# A Model for Assessing Waste Generation Factors and Forecasting Waste Generation using Artificial Neural Networks: A Case Study of Chile

---

A thesis
submitted in partial fulfilment
of the requirements for the Degree of
Master of Engineering
(Natural Resources)

At
Lincoln University
By E.A. Ordóñez-Ponce

---

Lincoln University
2004

Abstract of a thesis submitted in partial fulfilment of the requirements for the Degree of M.E. (Natural Resources)

# A Model for Assessing Waste Generation Factors and Forecasting Waste Generation using Artificial Neural Networks: A Case Study of Chile

**by E.A. Ordóñez-Ponce**

While the Chilean constitution guarantees the right of a clean environment and that environmental acts and policies to manage waste have been passed, waste generation has increased dramatically in the last decade in Chile and programmes to recycle, recover or reuse waste are not being implemented.

The extent of Chile's waste management problem is vast. Among the existing problems for implementing waste management programmes in Chile is the lack of information on factors contributing to waste generation and the absence of waste generation forecasts. Recognising these waste generation factors is essential for implementing policies to reduce waste generation and waste generation forecasts are fundamental for planning waste management systems. This research aims to design an analysis tool to assess waste generating factors and forecast waste generation for a significant portion of Chile.

Data for many variables indicating socio-demographic, economic, geographic and waste-related conditions was collected based on the existing literature. Using these variables, statistical methods identified Population, Percentage of Urban Population, Years of Education, Number of Libraries and Number of Indigents as the most important factors contributing to waste generation in Chile. A Multi-Layer Perceptron neural network modelled the relationship between these variables and waste generation with great

accuracy ($R^2$ = 0.819). The MLP network determined their respective contribution to waste generation and showed that they all contribute positively to waste generation.

Using these variables, a Self-Organising Feature Map neural network clustered the 342 communes of Chile into three groups (with 91, 156 and 95 communes) from which representative communes were selected for data collection for forecasting waste generation. The most representative communes were not used due to lack of data. Therefore, secondary representative communes were selected, reducing the level of representativeness of the model from 230 (67.3%) communes to 167 (48.8%). Data was collected from the secondary communes and forecasts for waste generation up to the year 2010 were made.

Recurrent networks were the best neural networks for forecasting waste generation using the selected variables for the three groups ($R^2$ = 0.75, 0.25 and 0.80, respectively). These results were improved using Multi Layer Perceptrons and recurrent networks with Per Capita Waste Generation as a new input ($R^2$ = 0.81, 0.91 and 0.98), showing extremely accurate forecasts for the validation periods. Forecasted rates show that by 2010, representative communes will generate 100, 240 and 2,900 tonnes/month, reaching annual rates of 1%, 0.6% and –3%, respectively.

The forecasted results were used to obtain estimates for the represented communes of each group. Total waste generation from the represented communes will peak at 3,800 tonnes/month and 18,500 tonnes/month by 2010 and over 330,000 tonnes/month by 2007. Extrapolating these results shows that Chile will peak at more than 500,000 tonnes/month by 2007, an increase of 7.6% in total waste generation from 2002.

Finally, it has been demonstrated that artificial neural networks have the potential to work with waste data to great accuracy despite the problems with the data. The proposed model represents a reliable tool for improving waste management not only for Chile, but also abroad.

Keywords: Artificial Neural Networks; Waste Generation; Clustering; Forecasting; Multi-Layer Perceptron, Self-Organising Feature Maps, Recurrent Networks, Chile.

# ACKNOWLEDGEMENTS

First of all I want to thank God not only for giving me the opportunity of doing this Masters, but also for giving me the great gift of life. Thank you for being always by my side.

I want to thank and dedicate this work to my beloved wife and friend Sole. You have always been by my side and have supported me all the way not only through this project, but through our wonderful project of life. Thanks for your love and understanding, for your cuddles and patience, for listening to me and taking care of me, for making me a better person. I love you very much.
This work is also dedicated to my son Tomás. You are the most amazing thing that has ever happened to me and I cannot express in words the love I feel for you. I will always do my best for your welfare. I love you very much.

I would also like to thank my parents and my brother and his family. You all have always been there for me. You have always supported me and have taught me the values of a family. I owned you my life, my education, my values. I love you all.

I also want to thank my supervisors Dr. Sandhya Samarasinghe and Lynn Torgerson. Your academic and personal support has helped me in the development of this work and I really appreciate your help. It has been a real pleasure having worked with you. Thank you very much.

I also want to express my gratitude to my in-laws who have supported us with their love, help and advice. Thank you for being always there for us.

I also want to thank our friends in New Zealand: Lavandero-Jerez, Rhodes-Díaz, Carabelli-Amicone, Marchand-Macci and Urrutia-Taverne. You have all been a very important factor in our life in New Zealand. I am sure that without all of you, this period would not have been as pleasant as it has been. You have all been as our family and we really love you and thank you for your support and for sharing your life with us. Thank you all and all the best. We will really miss you.

I would also like to thank my uncle Pato, my aunty Gina and my cousins Juan, Patty and her family. We are really grateful of your help and love. Thank you, all the best and we will think of you.

I want to acknowledge the contribution done to this research by the following people: Rudolfo Baeza (Municipality of Peumo), Ida Fuentes (Municipality of Purén), Jessica Mualim (Municipality of María Pinto), María Elena Valderrama (Municipality of San Joaquín), Patricio Villegas (Municipality of La Florida), Andrea Allamand (Municipality of Ñuñoa), Frank Radon (Unidad de Desarrollo Tecnológico, Universidad de Concepción), Cristian Olivares (Universidad del Bío-Bío), Roderick Gutiérrez (Universidad de Chile), Ximena Rojas (CONAMA-RM), Joost Meijer (CONAMA), Rene Fuentealba (ECOSFERA), Marta Zamudio (SESMA).

I would also like to thank the Natural Resources Group staff: Chris Gibson, Jane Swift, Don MacKenzie and Stefanie Rixecker for their help and support.

Finally, I want to express my gratitude to the New Zealand Agency for International Development (NZAID) for awarding me with this scholarship and Lincoln University for their contribution to this research.

It has been a real pleasure.

Eduardo A. Ordóñez Ponce
Lincoln, December 2004

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# CHAPTER 1

# 1. INTRODUCTION

## 1.1 Chile

The Republic of Chile encompasses more than two million square kilometres in South America, primarily along 4,200 km of the Pacific Ocean coastline, as well as in territories in the Antarctic and Oceania (Easter Island).

The People:

The population of the country exceeds 15 million, increasing at an annual rate of 1.2% since 1992. The urban population approaches 86.6%. The average age of population is 26.5 years. Population density is 20 people per square kilometre, with more than 40% of the population living in the Metropolitan Region[1] (Instituto Nacional de Estadísticas - INE, 2003). Less than half of Chileans are married and 70% consider themselves Catholic. The percentage of people with tertiary education has risen to 16.4% in the last ten years; the average number of years of education is 8.5 years and 95.8% of the population over the age of 10 are literate.

The Economy:

Chile has reduced its poverty level from 38.6% in 1990 to 21.2% in 2000, with less than two percent of the population living on less than US$1 (1993 PPP[2]) a day (United Nations Development Programme - UNDP, 2002). In 1987, the Gross Domestic Product (GDP) per capita was US$4,862 (PPP) (UNDP, 1990) and by 2002, it rose to US$9,820 (PPP) (UNDP, 2004). In 1990, inflation reached over 25% but was reduced to 5% by 1997. Foreign investment has increased from US$1.0 billion in 1990 to more than US$9.0 billion in 1999 (Banco Central de Chile, 2002a). The Human Development Index (HDI[3]) increased from 0.782 in 1990 to 0.839 in 2002 (UNDP, 2004). Total exports increased from US$8,373 million in 1990 to US$18,158 million in 2000, with copper as the most

---

[1] Chile is divided into thirteen regions for interior administration and government.

[2] Purchasing Power Parity

[3] Index developed by the United Nations, which measures three dimensions of the human development concept: longevity, knowledge, and a decent standard of living. Longevity is measured by life expectancy at birth; knowledge is measured by a combination of the adult literacy rate and the combined primary, secondary, and tertiary gross enrolment ratio; and standard of living by GDP per capita (PPP US$) (UNDP, 2002)

important resource (40%). Imports rose up to US$18,089 million in 2000 from US$7,742 million in 1990 (The World Bank Group, 2001).

## 1.2 Background Information

Chile's current constitution (1980) guarantees the right of every citizen to live in a pollution-free environment. The Government is charged with the role of safeguarding this right while protecting and preserving nature (Comisión Nacional del Medio Ambiente - CONAMA, 1997). In 1994 the Environmental Act was passed, establishing the first direct relationship between the state and the environment. There have been some further advances in Environmental Management. One example is the mandatory preparation of an EIA (Environmental Impact Assessment) for projects with the potential to harm the environment. In spite of the legal framework, authorities have found technical and economic barriers to implementing the law, as well as opposition from various interest groups.

The first Policy on Integrated Management of Domestic Solid Waste (DSW[4]) was formulated in 1997. The aim of the policy was to minimise the environmental impact of DSW management and eliminate negative effects on public health. A few Municipalities[5] started recycling programmes, incorporating a limited number of voluntary households for short periods of time. By 2001, 9.5% of DSW were recycled in Chile (CONAMA, 2002a), and the Metropolitan Region (MR), generator of 52.2% of the country's total residues, recycled 7% (Instituto del Medio Ambiente Gylania, 2001).

The amount of waste generated in Chile has had a dramatic increase over the last decade. Table 1.1 shows that in the period 1996-2002 the total amount of DSW generation rose 67.0% (with four regions increasing more than 100%) and per capita generation in Chile increased by 59.3%. In addition, 68% of the total waste generated in 2002 is from the three most populous regions (V, VIII and MR). Population, a variable widely supported as a waste generation factor, rose just 4.84%, with two regions (III, XII) experiencing even a negative growth. (Figure 1.1 shows the maps of Chile and South America).

---

[4] Domestic residue mainly composed of organic matter, food, paper, plastics and metals, which are basically generated in houses, offices, educational institutions, and from other sources such as cafeterias from industries and hospitals, which show similar characteristics to the residues generated in houses.

[5] Governing bodies of communes (towns with local government). There are 342 communes organised into regions.

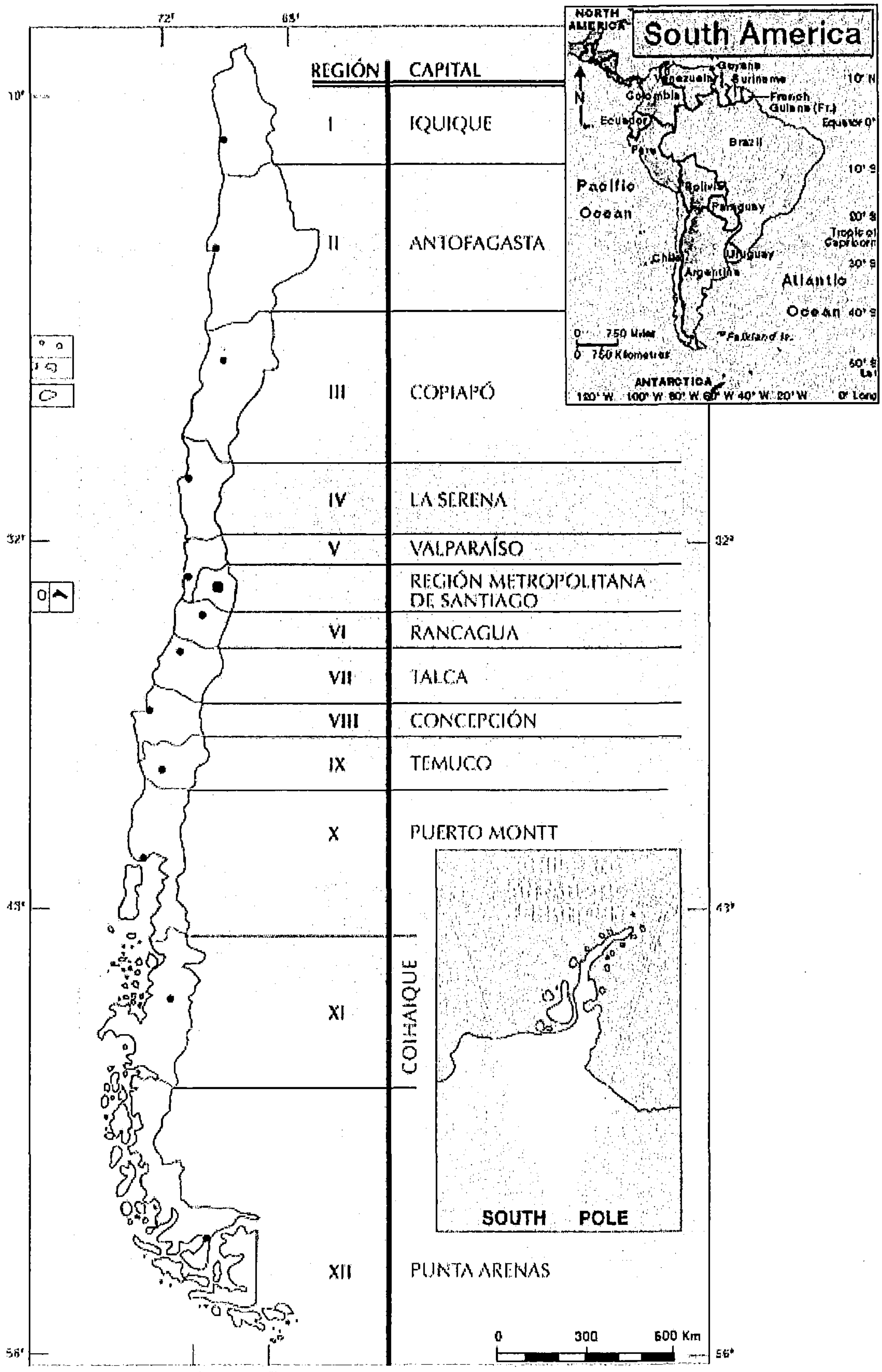



Figure 1.1: Maps of Chile (by Regions) and of South America

Table 1.1: Quantity of Waste Disposed of in Landfills or Legal Dumping Sites, the Amount of Waste Generated Per Capita per Day and Population per Region (1996-2002)

| Region | Waste Disposed (tonnes/year) | | | Population (people) | | | Waste Generation (kg/pc/day) | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1996 † | 2002 § | % Change | 1996 ¥ | 2002 ¢ | % Change | 1996 | 2002 | % Change |
| I | 83,880 | 115,879 | 38.15% | 373,064 | 428,594 | 14.88% | 0.62 | 0.74 | 20.25% |
| II | 102,240 | 309,704 | 202.92% | 443,340 | 493,984 | 11.42% | 0.63 | 1.72 | 171.86% |
| III | 55,080 | 98,658 | 79.12% | 255,039 | 254,336 | -0.28% | 0.59 | 1.06 | 79.61% |
| IV | 93,600 | 200,094 | 113.78% | 544,892 | 603,210 | 10.70% | 0.47 | 0.91 | 93.11% |
| V | 341,280 | 523,507 | 53.40% | 1,488,362 | 1,539,852 | 3.46% | 0.63 | 0.93 | 48.27% |
| VI | 106,560 | 208,212 | 95.39% | 747,827 | 780,627 | 4.39% | 0.39 | 0.73 | 87.18% |
| VII | 117,720 | 236,706 | 101.08% | 881,014 | 908,097 | 3.07% | 0.37 | 0.71 | 95.08% |
| VIII | 317,160 | 498,638 | 57.22% | 1,852,645 | 1,861,562 | 0.48% | 0.47 | 0.73 | 56.47% |
| IX | 115,920 | 202,649 | 74.82% | 836,292 | 869,535 | 3.98% | 0.38 | 0.64 | 68.13% |
| X | 140,040 | 263,738 | 88.33% | 1,016,711 | 1,073,135 | 5.55% | 0.38 | 0.67 | 78.43% |
| XI | 14,400 | 19,404 | 34.75% | 89,297 | 91,492 | 2.46% | 0.44 | 0.58 | 31.52% |
| XII | 30,240 | 127,550 | 321.79% | 152,688 | 150,826 | -1.22% | 0.54 | 2.32 | 327.00% |
| MR | 1,819,080 | 2,767,973 | 52.16% | 5,737,693 | 6,061,185 | 5.64% | 0.87 | 1.25 | 44.04% |
| Total | 3,337,200 | 5,572,714 | 66.99% | 14,418,864 | 15,116,435 | 4.84% | 0.63 | 1.01 | 59.28% |

† (INE, 2001a)
§ (CONAMA, 2003)
¥ (Banco Central de Chile, 1999)
¢ (INE, 2003)
Note: Chile has waste collection coverage of 99.2% (Johannessen & Boyer, 1999).

With the aim of improving above figures, CONAMA established the Environmental Agenda for the period 2002-2006. The agenda set a goal of disposing 80% of domiciliary waste in landfills by 2005 and 20% recycling rate by 2006 (CONAMA, 2002b).

### 1.3. Proposed Study

The extent of Chile's waste management problem is vast. This research focuses on two specific aspects of this problem. The first is the lack of knowledge about factors influencing waste generation. The second is the absence of appropriate predictions of waste generation. This research strives to find relevant solutions to these two aspects. The study is centred on DSW generation, which comprises 70% of total waste in Chile (Servicio de Salud Metropolitano del Ambiente - SESMA, 2002). In this study, only deposited waste (not recycled) is analysed.

### 1.4. Main Aim

The main aim of this research is to contribute to the development of sensible waste management practices and the improvement of DSW management in Chile, using information on quantity of waste and waste generating factors. In order to realise this goal, the following objective is formulated:

- Design a communal analysis tool to study waste generating factors and to forecast waste generation levels. This objective is divided into the following sub-objectives:
    1. Determine the factors contributing to DSW generation in Chile,
    2. Cluster groups of communes according to relevant waste generating factors, in order to simplify analysis,
    3. Select a representative commune per group for analysis and forecast its waste generation,
    4. Use representative communes' results to estimate future generation for the communes they represent and thus forecast waste generation for a significant portion of the country.

## 1.5 Research Justification

Currently, variables affecting waste generation in Chile are unknown due to the absence of adequate and thorough waste generation information. Waste reduction policies cannot be implemented until the variables affecting waste generation are identified. Without understanding the critical variables, minimisation policies may not be relevant and consequently, may be unsuccessful. Unless these variables are recognised, it becomes difficult to estimate future generation of waste properly.

Estimates of future waste generation are the basis of planning and operation of solid waste management systems. Environmental authorities need to have accurate information to define landfills capacities and operating life, establish sensible recovery programmes and design waste collection, transport and disposal systems. Waste management can be planned more effectively if waste generation predictions are available and reliable.

The results obtained from this research can be used to develop a waste information system in Chile. This information system can provide data to design and enhance plans and programmes to manage residues at all levels. This is compatible with the waste management aims that CONAMA is trying to achieve (CONAMA, 2002c).

## 1.6 Research Method

The method has been divided into three stages (Figure 1.2):

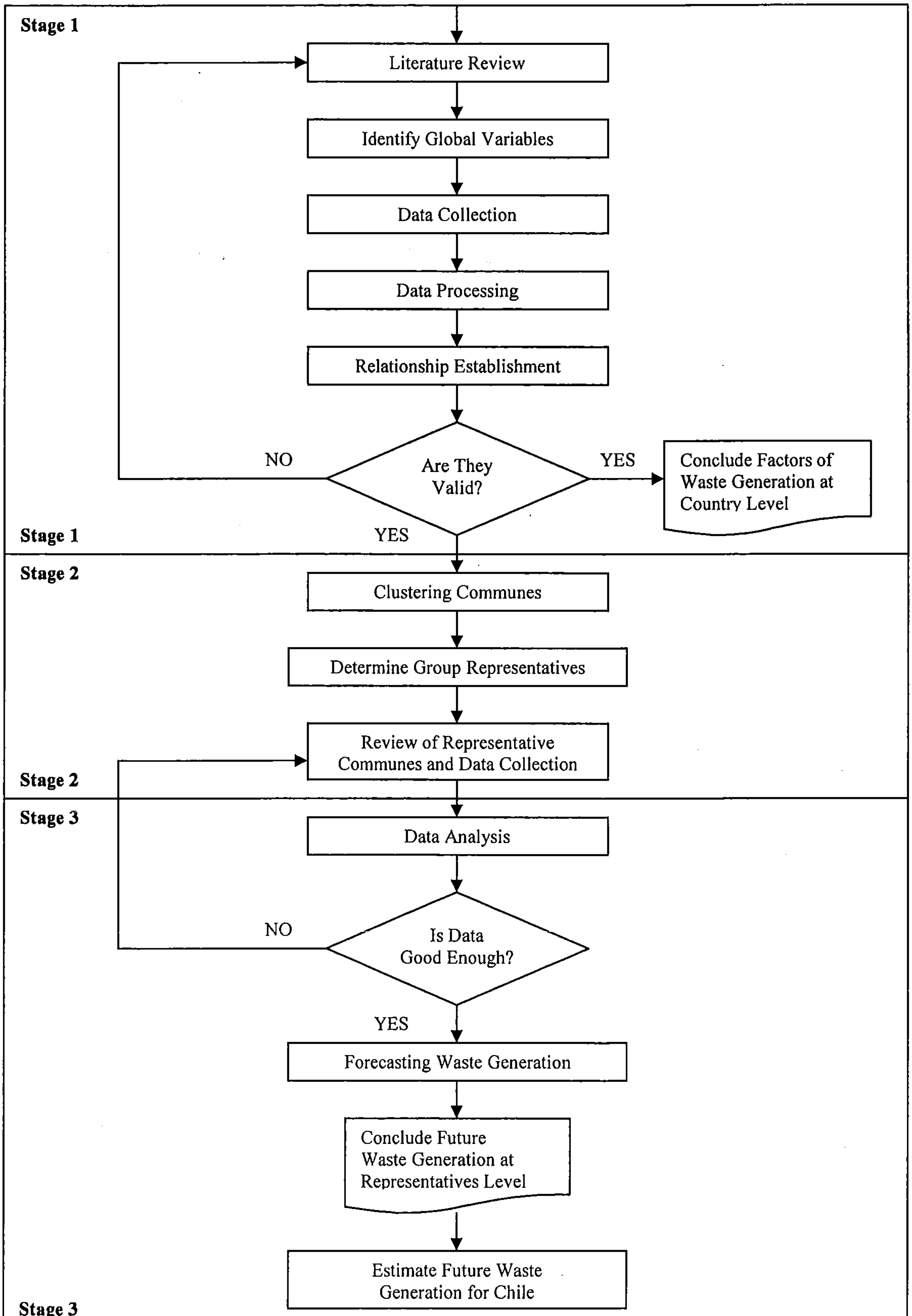



Figure 1.2: Flowchart of Stages of the Proposed Research

The research method has been designed with the aim of being applicable to any territorial administrative division (country, region, province, commune, district, etc.) that generates waste as an independent unit. The case study is focussed on Chile and its 342 communes. Appendix 1 shows maps of the communes and regions of Chile.

### *1.6.1 Stage 1: Determining Waste Generation Factors and their Relationship to Waste*

The process of finding relevant information to determine the factors affecting waste generation in Chile is developed in several and distinct phases. Presented below is an overview of the process.

- Literature Review:

  In this phase, detailed analysis of topics such as waste management and its generation, recovery programmes, landfill operations, environmental policies, environmental consumerism, recycling activities, recovered materials markets and waste predictions is conducted. From this analysis, factors widely identified as waste generating factors are closely examined in the Chilean context and relevant variables are selected and considered as global variables.

- Identify Global Variables:

  Global variables are determined as part of the literature review phase outlined above. They can be classified as socio-demographic, economic, geographic and waste-related variables. These variables and associated data are available at the communal level in Chile.

  Examples of global variables are:

  - Socio-demographic: population, population density, household density, number of households, education level, age groups, level of urbanism, gender and occupation of the head of the family;
  - Economic: income level per family, expenditure on groceries and electricity consumption;
  - Geographic: climate and geographical location;

- Waste-related: waste generation levels, waste composition, disposal fees, existence of recycling programmes and quantities recycled.

- Data Collection:

  Data on global variables can be sourced from a number of locations in Chile. Census data or economic indicators are obtained from public institutions including the Central Bank of Chile, the National Institute of Statistics (INE), the National Commission for the Environment (CONAMA) and relevant Ministries. Data is also collected from publications online and via contacts at the institutions.

- Data Processing:

  The collected data is statistically analysed searching for multicollinearity and heteroskedasticity problems among the variables. Thus, all unrelated variables are left aside due to their irrelevance. Any highly correlated variables are also omitted as their effect on the output may be achieved through some other variable(s).

  - Multicollinearity means that the explanatory variables are highly correlated, making it difficult to separate their respective effects on the explained variables. Pair-wise correlations are run among all variables and those pairs with correlations greater than 70% are considered highly correlated (Ali Khan & Burney, 1989; Lee, Semester 1, 2003). The least correlated variables are selected as explanatory variables.
  - Heteroskedasticity causes large variances and loss of precision in the model. Some of the tests available for detection are Anscombe (RESET Test), White Test, Glejser Test, Goldfeld & Quandt Test and Breusch & Pagan Test. The individual tests are applied according to the type of data, type of variables and the number of observations. If heteroskedasticity is detected, the Two-Step Weighted Least Squares Test or the Goldfeld & Quandt Test are available to solve the problem (Maddala, 2002).

- Relationship Establishment:

  Artificial Neural Networks are run to determine the best model relating the selected explanatory variables to waste generation. A Multi Layer Perceptron is capable of modelling waste generation and determining the contribution of each explanatory variable to waste generation.

A trial and error process is adopted until the highest coefficient of multiple determination ($R^2$) and the lowest mean square error (MSE) are found among the trained networks. Both equations are shown below (Eqs. 1.1 and 1.2). An $R^2$ value compares the accuracy of the model to represent real output values. A perfect fit would result in an $R^2 = 1$, a very good fit near 1 and a very poor would be less than 0. MSE is a statistical measure of the differences between the real outputs and outputs predicted from the network. MSEs are compared among the trained networks and the lowest is selected. If $R^2$ becomes poor, the process returns to the Literature Review and searches for more and/or better variables to explain the sought relationship.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad \text{(Eq. 1.1)}$$

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{2 * n} \qquad \text{(Eq. 1.2)}$$

$y$: real value;

$\hat{y}$ :predicted value of $y$;

$i$: number of observations (from 1 to n);

$n$: total number of observations.

Upon completion of this step, waste generation factors are defined at the country level. This concludes Stage 1.

### *1.6.2 Stage 2: Clustering of Communes and Selection of Representative Communes*

Based on the selected waste generation factors in Stage 1, communes are clustered. From these clusters, representative communes are selected for analysis. The purpose of this selection is to simplify the data collection and subsequent analysis.

- Clustering Communes:

The 342 communes of Chile are clustered into *n* groups based on the variables found in Stage 1. These variables are the inputs to a Self-Organising Feature Map (SOFM) neural network that clusters the data. The number of groups is determined based on the ability of the network to cluster the communes according to specific properties of the input data.

- Determining Group Representatives:

From each of the *n* groups obtained from the cluster analysis, a representative commune is selected per group. The representative commune is one that represents the most number of communes in its group according to the selected variables. Using this representative commune, further research is developed. Ideally, this commune should be the most representative of the group as it will improve the applicability of results to other communes within its group.

The criterion to determine each group's representative is based on the capacity of the commune to cover the largest possible number of communes in its group within a ±15% range of its values for the variables found in Stage 1.

- Review of Representative Communes and Data Collection:

Selected representative communes are contacted and visited. This ensures direct access to operating systems and processes of waste management authorities and Municipalities, and facilitates the development of realistic and relevant approaches for waste assessment in Chile.

Data on waste generation and the variables that can contribute to waste generation need to be collected from the representative communes. Waste generation data should be available from local Municipalities through their respective Waste Departments, CONAMAs and Regional Health Services, and socio-demographic and economic data should be available from public institutions. Research developed by local/national/international agencies can also add important information to complement the data obtained from authorities. All these data need to be arranged historically to create a dataset that supports the aim of making future predictions.

This concludes Stage 2.

### *1.6.3 Stage 3: Forecasting Waste Generation*

Collected data is analysed and predictions of future waste generation for representative communes are made. These are then used to obtain estimates of waste generation for the represented communes and for the whole country.

- Data Analysis:

  Collected data must be analysed to determine its suitability for the research. Collecting an adequate amount of data is important to supply a good dataset for the network. The aim is to feed the network with data from a set of years for all the Stage 1-relevant variables and waste generation levels for the same group of years for every representative commune.

  If there is lack of information from the representative communes or if there is not enough data to make predictions, other similar communes could supply data. These communes should be contacted and information collected either to complement or supplement the information on the representatives. As with the original selected representatives, these other communes must be as representative as possible based on the same original criterion.

  The degree of representativeness of the proposed model depends on the quantity and quality of data collected from the communes. The best possible scenario is when only data from the representative communes is used in the predictive network. If data from alternative communes is used, the coverage range of the model decreases. The degree of representativeness of the commune supplying the data is the criterion determining usefulness of its data.

- Forecasting Waste Generation:

  Based on the explanatory variables previously selected and on the collected data, predictive models are run to forecast amounts of waste generation for the representative communes and use the predictions to estimate waste for the *n* groups.

Multi Layer Perceptron and Recurrent Networks are trained in the prediction of future waste generation with different combinations of inputs (variables), neurons and layers. A trial and error process is developed until the highest coefficient of multiple determination ($R^2$) and the lowest mean square error (MSE) are found (Eqs.1.1 and 1.2, respectively).

- <u>Estimate Future Waste Generation for Chile:</u>

  Finally, future amounts of waste generation for the communes represented in every group are determined in relation to that of the representative commune and an overall estimate for the country is obtained.

  This concludes Stage 3.

# CHAPTER 2

# 2. LITERATURE REVIEW

### 2.1 Waste Generating Factors

In the past, various researchers have studied variables related to waste generation. Although most research focuses on objective variables, some researchers have analysed non-parametric factors such as emotions and preferences in the scope of their research.

Despite the intrinsic biases and points of view expressed on subjective factors, some researchers have examined aspects such as recycling behaviour and green consumerism. Folz and Hazlett (1991) analysed recycling behaviours and found that the success of a recycling process is not dependent on socio-economics or communities' political characteristics but on the adopted policies. Williams and Kulik (1992) established that cultural differences such as pressure to recycle, conservation ethos, powerful traditions and homogeneity can have a crucial effect on recycling. Scott (1999) found that some individuals recycle due to social pressure, while for others, the satisfaction from their environmentally responsible actions is more important. Conversely, he claimed that neither environmental motivation nor the desire to minimise landfills and their impacts were related to recycling behaviour. Furthermore, Chu and Chiu (2003) found that even though there has been an official recycling programme in Taiwan, there is still resistance from citizens, and political complexity and cultural problems have made the system work inefficiently. They concluded that a household's moral obligation improves the intention of recycling. On green consumerism, Mainieri, Barnett, Valdero, Unipan and Oskamp (1997) found that consumer beliefs, environmental attitudes and resource conservation activities were the most significant factors affecting green consumerism. Furthermore, Ebreo, Hershey and Vining (1999) stated that measures of environmental concern, recycling attitudes and recycling motives are related to a product's toxicity and packaging.

On the other hand, objective variables have been found to behave in different ways depending on the place of study, the community's features or the method used in their analyses.

Past researchers have focussed on different sets of variables, but population and income are the most considered, although with inconclusive results as to the relevance to waste generation.

In 1974, Grossman, Hudson and Marks analysed the demand for waste collection services in relation to population and income levels, as well as the size of dwelling units, home valuation and education level. In addition, subjective variables such as environmental concern and cultural characteristics were also examined. However, they concluded that waste production occurred independently of the analysed variables and that these were not significant for the assessed community. More recently, Bagby, Ernsdorff, Kipperberg and Perrin (2001) developed models as part of Seattle's Solid Waste Plan which used population, number and size of households, employment by sector, household income and construction activity to project future waste stream but found little growth in waste generation due to Seattle's characteristics. In contrast, West Virginia Solid Waste Management Plan stated that demographics, including population as well as income, determine the waste that is generated.

In 1993, McBean and Fortin considered population, among other variables such as number of households, to be essential for their forecasting model of refuse tonnage. According to Hockett, Lober and Pilgrim (1995), population was the "overriding variable influencing total waste generation". Hamburg, Emdad Haque and Everitt (1997) estimated waste generation rate to be related to population size. The United States Environmental Protection Agency (1997) determined that population, employment and taxable transactions, "were the strongest predictors of waste generation". On the contrary, Rachdawong, Khaodhiar and Sangiampaisalsuk (2000) found that electricity consumption "exhibited the strongest correlation to solid waste generation rates in Bangkok", in comparison to population and gross provincial product.

Population has also been measured in different forms. Nagelhout, Joosten and Wieringa (1990) used the effect of population growth and consumption as determining factors to project different waste categories. Williams and Kulik (1992), analysing cultural differences, discovered that high population densities could have critical effects on recycling progress. Later, Cailas et al. (1996), proposing an indicator of solid waste generation potential, examined population density together with percent of urban population, percent of persons with high education level, number of households, employment rate and the total number of taxable transactions. Cailas et al. (1996) concluded that all these variables are highly correlated with the variables quantifying the residential, municipal, commercial/institutional components of the waste stream.

Conversely, other authors have found income to be more relevant than population. Ali Khan and Burney (1989), who contemplated population as one of their variables, detected that income, as well as temperature and dwelling occupancy rate were the three factors that affected the percentages of solid waste components. In 1993, Chang, Pan and Huang concluded that "... population [was] less important statistically when the average generation rate is predicted", stating that real income is "... the most influential factor on waste generation". Moreover, SystemAnalysis[6] (1998) pointed out that "material flow is regulated largely by net income and less by present population". More recently, Buenrostro, Bocco and Vence (2001) analysed the effects of monetary income, density of dwellers per household, education level and age in the generation of residential solid waste. They stated, "In Morelia [Mexico], the variables which were found useful for forecasting the generation of waste were monetary income and density of dwellers per household". However, Hockett et al. (1995) observed that income, among other variables, was not significant in predicting per capita waste generation. They found that the significant determinants of per capita waste generation were per capita retail sales and tipping fees. Furthermore, Bruvoll (2001) claimed that in her study, "the overall quantities of municipal solid waste are not influenced by income" but by landfill fees.

Income has also been analysed together with less conventional variables. Arey, Baetz, Macdonald and Byer (1993) studied income along with geographical location, climate and local ordinances and determined that these variables affect waste generation. In 1994, Kerzee, Cailas, and Swager included median family income, household size, persons per household, home lot size, number of households with air conditioners and the community's annual average temperature. They found that the percentage of adults educated above the high school level, median age and percent of population employed and of population living in urban areas influence solid waste generation in Illinois, USA. In

[6] SystemAnalysis is a project focussed on assisting public and corporate policy makers in taking decisions. It applies advanced technologies and techniques in order to increase rationality and awareness of decisions and management. http://www.geocities.com/ResearchTriangle/Thinktank/1036/index.html

1998, Koushki and Al-Khaleefi analysed information on family size, employment, income, car ownership, occupation, education and age of the head of the family, the type of residence and the number of weekly family shopping trips. They concluded that all these factors affected the daily quantity of solid waste generated by families.

Though the relevance of gender is not clear, the percentage of male and female population has been considered in some studies. Sundeen (1988, cited in Folz and Hazlett, 1991) found that gender was not a good predictor of the propensity to recycle voluntarily on a study on urban wastes. In addition, Vining and Ebreo (1990, cited in Scott, 1999) "argued that recyclers and nonrecyclers did not differ in terms of education, gender, or household size". On the contrary, Ebreo et al. (1999) stated that gender had been linked to increased environmental concern and concluded that it was strongly related to Conservation and Kind-to-Nature attributes.

Despite the large amount of literature related to waste, not many studies have analysed middle or low-income countries. Nevertheless, a study of the Chicago area by Howenstine (1993, cited in Margai, 1997) suggested "the fact that drugs, crime, poverty and unemployment in poor ethnic neighborhoods may be among the barriers to residential involvement in environmental activities".

As mentioned previously, Rachdawong et al. (2000) analysed electricity consumption as one of the study variables. A study conducted in Chile on waste generation also examined electricity consumption as one of the explanatory variables and found that it is strongly related to the generation of per capita domiciliary solid waste (Orccosupa, Arellano, & Figueroa, 2002).

Finally, the existence of disposal fees has been considered in several studies and they all conclude that it is a factor that induces a reduction in the generation of residues. In agreement, Hong, Adams and Love (1993) claimed that, "increases in disposal fees encourage recycling". Moreover, Hockett et al. (1995) determined that having a tipping fee is relevant to waste management, highlighting its value in controlling waste generation. However, they also concluded that this finding "indicates the relatively small importance of demographic variables relative to structural ones in determining waste generation". Similarly, Bruvoll (2001) stated that "Landfill fees reduce the waste landfilled and increase recycling and incineration".

## 2.2 Waste Generation Models

Different authors have attempted to predict waste generation produced by communities of all kinds, groups of households, total population of a country or cities worldwide. The methods used are mostly associated with predictive statistical tools such as regression analysis or time-series models. However, non-statistical approaches such as fuzzy models, mathematical techniques or computer simulations have also been used.

### *2.2.1 Regression Analysis Models*

Shell and Shupe (1972) developed a regression analysis model as part of a study to estimate present and future generation rates of solid waste for municipal, commercial, institutional, industrial and agricultural waste generators. The study collected data for residential variables from 45 sub-districts in Cincinnati, Ohio, USA (1969) and conducted a linear regression analysis on that data. The model attempted to determine pounds of waste per week per district by analysing variables such as the number of stops for collection, number of families, the number of single building dwelling units, population and income. The final result showed that the number of stops for collection was the most significant variable, followed by number of families and single-building dwelling units. However, the explanatory variables do not properly clarify their significance on waste generation.

Grossman et al. (1974) developed a similar prediction method attempting to estimate gallons of waste produced per week in Brookline, Massachussettes, USA. According to the conclusions and the vague statistical results, this model neither explains nor predicts, in a proper manner, future waste generation. It concluded that waste production occurred independently of the analysed variables and that these were not significant for the assessed community.

In 1989, Ali Khan and Burney wanted to forecast recovery waste components with "easier and simpler models". They used socio-economic factors and the industrialisation level of 28 cities from industrialised, middle and low-income countries. Variables from different groups were selected to generate regression analysis models, leaving one or two cities for validation. However, although they reached some important conclusions, the procedure of mixing extremely different cities from around the world to generate a single explanatory model cannot be wholly justified due to contrasting waste generating conditions in different countries. For example, the income of Jeddah was put together with that of Manila (which is twenty five times smaller); Jeddah's 28°C temperature with Bonn's 9°C and the figure of 7 persons per dwelling in Tokyo with Stockholm's $^{7}/_{3}$ per dwelling. Furthermore, a maximum of 18 observations were considered to estimate the models, which is a small sample. Ali Khan and Burney (1989) concluded that income, temperature and dwelling occupancy rate affected the percentage of waste components.

A different technique was developed by McBean and Fortin in 1993. The aim of their research was to design a forecast model of refuse tonnage with recapture and uncertainty bounds for data from the region of Waterloo in Ontario, Canada. First, a coefficient-based model was developed based on an equation which subtracted total recaptured material from total waste. The model predicted types of materials but showed large variations in the predictions due to population growth. The model did not consider the dynamic interactions between waste generation rate and economic activity. Afterwards, a second model included socio-economic independent variables and the number of households to estimate total waste amount from regression analysis. This second model was a better predictor since it considered the influence of economic activities on total waste, but it did not predict waste components.

Buenrostro et al. (2001) also used a regression analysis model in a case study in Mexico. They concluded that income and number of dwellers per household were relevant variables, however the model showed that these variables were of limited value in explaining solid waste generation. Moreover, the data was collected during the spring period, making estimations only valid for such season, reducing the model's forecasting capacity for another period.

Finally, Bagby et al. (2001) developed regression analysis models as part of Seattle's Solid Waste Plan. The purpose of their study was to forecast the amount of waste generated in the city based on its historical data on waste disposal and recycling. The predictions were subject to economic and demographic variables. Results showed very little growth in waste generation over the forecasted period (until 2014) mainly due to

Seattle's characteristics such as a continuing decline in the average household size or trends in the housing markets. The authors concluded that the model is not "directly transferable" to other places, mainly because the system has been designed specifically to Seattle. One of the model's assumptions is that waste generated was equal to recycled plus disposed waste. Therefore, in a place with no recycling data, the model would be inappropriate and ineffective.

### *2.2.2 Time-Series Analysis*

Some researchers have used Time-Series analysis with better results. In 1986, Bridgwater developed time-series analysis with the objective of making projections for up to fifty years. The main finding was that S-curves give the best results by regression analysis, a concept that included social, economic and technical trends, assuming the continuity of such trends. Such assumptions are among the limitations found in this approach. Certainly, continuity of trends would have been altered by further policies or natural adaptation of societies to new situations and activities. Furthermore, according to the author, S-curves tend to decay to a constant value in long-term predictions.

In attempting to establish the time effect of explanatory variables in waste generation, Chang et al. (1993) used geometric lag time-series analysis (Koyck model) for the period 1981-1990. The aim of their research was to evaluate future demand for waste collection services and estimate the proposed design capacity of incinerators and landfills in Pa-Li, Taiwan. The variables analysed were average waste generation per capita per day as the dependent variable and total population, consumer price index and average per capita income as explanatory variables. It was not specified why these were considered. Four time-series models were analysed and the Unconditional Least Square Estimation (ULS) model was accepted as the representative model for the research. A negative relationship was found between average waste generation per capita per day and total population, which according to the author, was explained due to a period of population mobilisation (two years) that reduced a steady positive trend in population growth in the previous years to –7%. However, it is not clear if other external factors may have influenced the mentioned negative relationship.

Bruvoll and Ibenholt (1997) developed an economic model to forecast manufacturing industries waste generation in Norway. The predictions were based on the use of tangible factor inputs such as capital, labour, material input, use of energy and transport and production levels. The production and input factors were calculated using a multi-sectoral equilibrium model (MSG-EE) developed with data from the period 1962-1989, in which total production growth was largely determined by technological change, growth in real capital, labour and the supply of raw materials and natural resources. The model concluded that despite technological progress, an increase in waste exceeds growth in production and in the gross domestic product. The results are subject to the presumption of no additional actions to modify the existing trend in that period. Moreover, there are too many assumptions in MSG-EE: demand equals supply; domestic producer prices equal sectoral unit costs; intertemporal theory is not considered (saving versus consuming theory); firms behave competitively; constant returns to scale technology; and exogenous technological and organisational progress, all hypotheses which make the model unreal.

Another time-series approach was developed in 1997 by Chang and Lin. This time, the importance of recycling in predicting solid waste generation was analysed. ARIMA (Auto Regressive Integrated Moving Average) was applied to monthly time-series data for twelve administrative districts of Taipei City (Taiwan) from 1990 to 1995. Findings showed that recycling, as a policy, is important in the prediction of waste. Chang and Lin (1997) stated that recycling "resulted in a significant amount of uncertainties in the future forecasts" and that "it is dangerous to extend the model much beyond its range of estimation". Results indicate that if recycling is homogenously applied in the twelve analysed districts, there may be a 16% reduction in waste generation in the city of Taipei (based on a 95% confidence interval). The prediction is based on previous trends in waste generation without including any other variable, thus assuming that these effects are captured in the past waste data. The model analysed only recycling as a probable intervention to the system, leaving the consideration of other variables for future research.

Finally, in 2002, Navarro-Esbrí, Diamadopoulos and Ginestar analysed waste generation based on monthly and daily waste collection time-series data from the municipalities of Thessalonoki, Greece and Valencia and Castellon, Spain, using sARIMA (Seasonal ARIMA) and a non-linear technique. The authors concluded that both methods gave good results in terms of predictive accuracy and cumulative errors. The sARIMA model is a very complete procedure, detecting and eliminating non-stationarity as well as any possible cycles and/or seasonal behaviour. Once the time effects were eliminated, an

AutoRegressive Moving Average (ARMA) model was used to represent the transformed time-series and later, through mathematical calculations and autocorrelation function (ACF), the forecasting model was determined. Although time effect was removed, which may modify some logical patterns because waste generation is in fact seasonal, this model makes quite good predictions as it was supported by the estimated calculations for monthly data of Valencia and daily data of Thessaloniki. Furthermore, the non-linear dynamic technique, basically for non-linear and non-stationary untreated data, gave results as good as the ones obtained by sARIMA. Nevertheless, as the authors mentioned, the key in the process is the selection of the appropriate dimensionality of municipal solid waste as a dynamic system and the differential mathematical functions of the generating model to be used (not an easy or simple process).

### *2.2.3 Other Approaches*

In 1998, Koushki and Al-Khaleefi studied solid waste magnitude, type and forecasting models for Kuwait. The aim of their research was to determine and analyse urban solid waste management cost-effectively. A random sample of 2,000 households was chosen and residents of four different areas were interviewed from October 1994 to May 1995, as well as collector truck operators and landfill staff. Four different methods were used for research: household questionnaires, survey data, truck survey data, and the municipality's landfill data. Frequency, mean and standard deviation of variables such as family size, employment, income and car ownership, as well as the head of the household occupation, education and age were analysed. Then, to examine the contribution of these factors to solid waste generation, a variance component analysis was performed. From this analysis, Koushki and Al-Khaleefi concluded that education and employment contributed insignificantly to solid waste generation. On the contrary, car ownership and family size contributed the most to waste generation. To forecast waste generation, three two-variable cross-classification models were considered due to their "practicality and simplicity of use". The models related households' solid waste generation to monthly income, family size or to number of persons employed per household, respectively. It was found that an increase in any of these three variables was accompanied by an increase in solid waste generation. According to the authors, "the forecast of only one household-related variable (income size, employment, or education of family head) is needed to predict the quantity of daily solid waste generated by a family". They argued that this "low-data-dependence characteristic ... is of significant importance, since the non-availability of data in developing nations often precludes the application of most forecasting models". However, analysing just one variable at a time would create a totally isolated system. There may be other important variables whose effects would not be captured by the model, thus providing just the relationship between one explanatory variable and waste generation levels. Future amounts of waste cannot be accurately predicted with these models.

A new technique to manage the problem of low data availability in developing countries was developed by Chen and Chang in 2000. Their study used a grey fuzzy (GF) dynamic model for the prediction of solid waste generation in the city of Tainan, Taiwan. Amounts of solid waste generated in Tainan City from 1985 to 1998, on an annual basis, were the variable used as input. The model is a good predictor of waste generation for the case of Tainan in the cited period of fourteen years. The authors claimed that three is the minimum database size to apply a GF modelling analysis, however with such a small sample, predictions would be limited to a very short time period. It is doubtful that trends could be represented by such an approximation.

Finally, Li, Zeng, Wang and Liu (2003) predicted amounts of urban solid waste in Loudi City, China by applying a gray theoretical model through non-linear differential equation simulation. The data used was annual amounts of solid waste produced in the city from 1990 to 1998. The least squares method (LSM) was used in estimating the model parameters and this was validated with data from the last two years. In the end, they concluded that the model was successful in predicting waste generation and predicted the amount of waste to be produced by the city in the next thirty years.

## 2.3 Artificial Neural Networks

### *2.3.1 Introduction*

Artificial Neural Networks (ANNs) are simplified computational models of the brain (Pham & Liu, 1995). They attempt to emulate some of the functions of the brain such as learning from experience and the capability of solving problems by using, modifying and extrapolating acquired knowledge. Neural networks are capable of classifying patterns (assigning observations to classes); clustering (data categorisation); approximating functions (scientific modelling); forecasting (time-series prediction); optimising results from an objective function (optimum resource allocation); and controlling inputs such that a system follows a desired trajectory (systems-control) (Jain, Mao, & Mohiuddin, 1996).

An ANN is formed by a large number of processing neurons that are interconnected by weights, which represent the influence of one neuron on another. ANNs have been classified into feed forward and recurrent networks. In a feed forward network, neurons are grouped into layers, and the signals flow from one layer to another in the forward direction. Multi-Layer Perceptron (MLP) is an example of feed forward network (Figure 2.1 (a)). A typical MLP network consists of an input layer, a hidden neuron layer and an output layer of neurons. Input layer simply transmits inputs (and a bias input) through weights to hidden neurons where weighted inputs are accumulated and processed by a transfer function to generate an output to be sent to the output layer. A similar process takes place in the neurons in the output layer where outputs are generated. This organisation gives ANNs the capacity to model complex problems, such as non-linear pattern classification and prediction. In a recurrent network, the flow is forward and backwards. In recurrent nets for time series forecasting, outputs of some neurons are fed back to the same or other neurons in preceding layers. The Elman and the Jordan nets are examples of recurrent networks (Figure 2.1 (c) and (d)). In Elman networks, hidden layer outputs are fed back to the input layer for processing in the next time step and in Jordan network, output layer output is fed back to the input layer. This feedback helps incorporate temporal effects into recurrent networks. Self Organising Feature Maps (SOFM) are a type of recurrent networks called competitive networks. Here, the input layer transmits data to the output layer neurons that compete by feeding their output back to the neurons in the same layer in order to inhibit them (Figure 2.1 (b)). The winning neuron represents the particular input and over time, various neurons specialise in recognising input patterns clustered in the input space.

ANNs are modelled via a learning process which can be supervised or unsupervised. In supervised learning, the network is presented with the inputs and target outputs iteratively and the network adjusts its weights using efficient learning methods such as steepest descent. The aim is to minimise the error in order to generate outputs as close as possible to the targets. Examples of supervised networks are MLP and Recurrent Networks (Figure 2.1 (a, c, d)). Conversely, unsupervised learning uses no external supervision and clusters the data presented to the network based on the properties of the data in a self-organising manner. An example where unsupervised learning is used is SOFM (Figure 2.1 (b)). As shown in the Figure 2.1 (b), multidimensional data are projected onto a 2-dimensional map where similar input vectors form clusters in the course of learning. In this research, the relationship of the selected variables with waste generation is developed using an MLP, SOFM are used for clustering of communes, and waste prediction models are developed using MLP and recurrent networks (Elman and Jordan) (Figure 2.1 (c) and (d), respectively). The software used is NeuroShell 2 – Release 4.0 (1993-1998) by Ward Systems Group®, Inc.

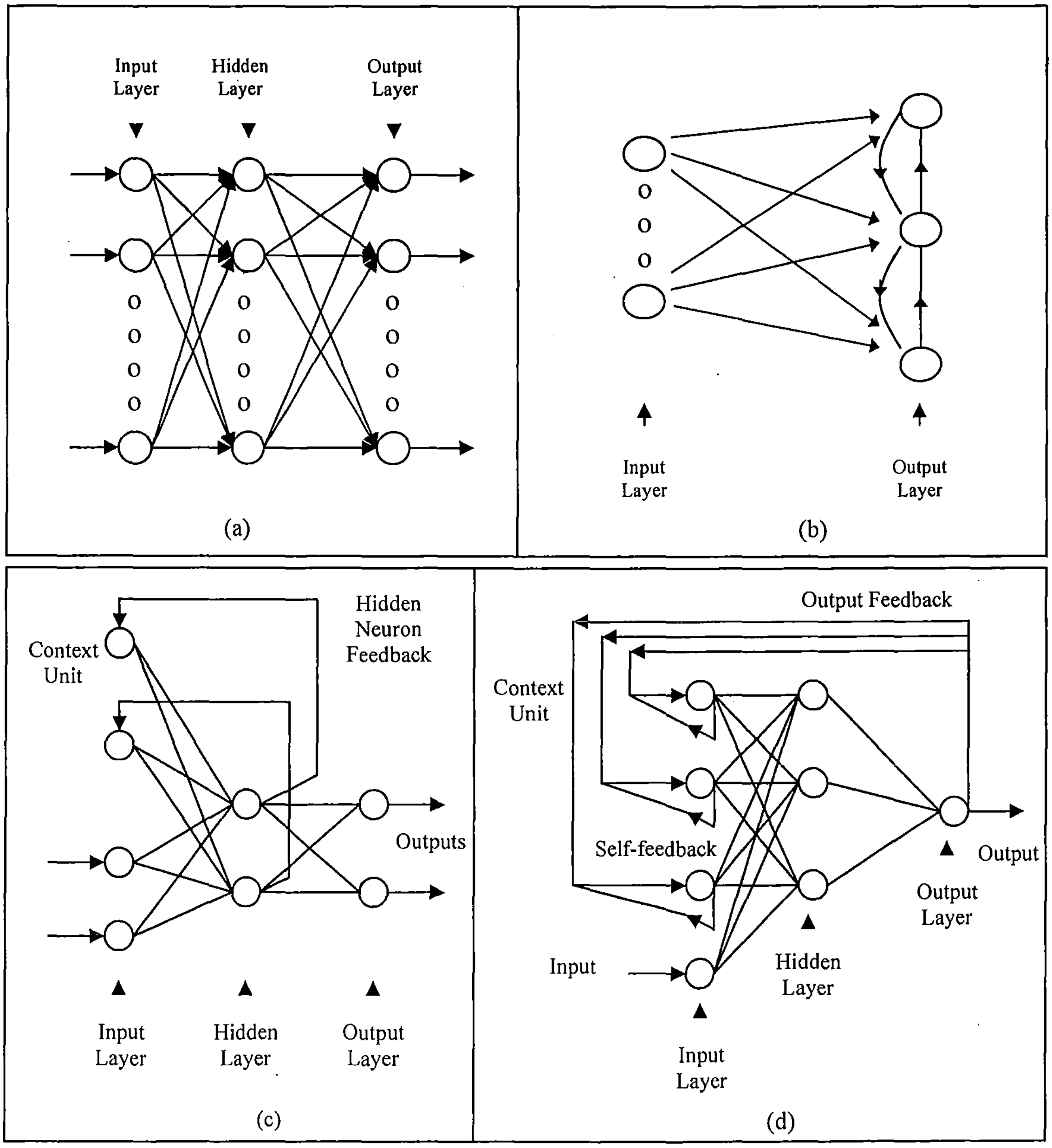



Figure 2.1: Types of Artificial Neural Networks. (a) Multi-Layer Perceptron (MLP), (b) Self-Organising Feature Map (SOFM), (c) Elman, (d) Jordan.

The dataset is divided into three distinct sets. The training set is used to train the network, the testing set is used to assess the model at various stages of training and the validation set is used to test the model predictions on unseen data (generalisation). In the evaluation process, the best networks are selected based on the highest coefficient of multiple determination ($R^2$), (Eq. 1.1), and the lowest mean squares error (MSE), (Eq. 1.2).

Artificial Neural Networks is a relatively new research field and is rapidly growing in popularity as evidenced by the proliferation of neural networks applications in virtually all fields of research. Their flexible and adaptive nature makes them very powerful predictors and classifiers and enable them to model any non-linear function to any degree of accuracy (Smith, 1996).

### *2.3.2 Artificial Neural Networks Research on Waste*

Neural networks have not been used for solid waste analysis. However, in 1998, Calderón, Espuña & Puigjaner used ANNs for waste analysis and minimisation in batch reactor operation. The networks were used as a "way to deal with complex industrial-sized problems to model the system based on historical input/output data". The networks were trained with inputs such as operation parameters, physical and chemical properties and process conditions; and the outputs were chemical process characteristics such as temperature, concentration, energy consumption, kinetic parameters, etc. In order to test the proposed methodology for modelling the operation of a batch reactor and the ways the batch reactor produces waste, three different situations were selected. A three-layer network showed good performance for the range of reactions in the training set.

Several studies have used ANNs in the field of wastewater treatment plants. El-Din and Smith (2002) worked with neural networks to predict the quantity of wastewater flow entering a wastewater treatment plant during storm events. A feed forward network with back-propagation as training algorithm was built in a systematic way so the model was able to learn and not memorise from past data and generalise to new unseen data with excellent results. In 2003, Hong, Rosen & Bhamidimarri used an SOFM to analyse the multi-dimensional data of a wastewater treatment plant and to establish the relationship of the process variables in an activated-sludge plant. Thirteen variables (components) were collected from the plant to create the map. Then, component planes (a data presentation tool) were placed serially to analyse the dependence between components. Thus correlations among components were determined through visual examination of the component planes. Finally, five groups were established by visualisation of two matrices (U-matrix and median D-matrix) that show the distances between neighbouring nodes. It was concluded that the network was able to cluster complex relationships between the process variables without previous knowledge of the processes occurring in the plant. Furthermore, the network was found to be a useful tool in the diagnosis of the activated-sludge plant. Hong et al. (2003) also stated that "the components planes and the cluster analysis by U-matrix and median D-matrix in the SOFM show some detailed local relationship between the variables, e.g., responses of the process variables under different operating conditions as well as the global information". In 2004, Hamed, Khalafallh & Hassanien worked with neural networks to predict the performance of a wastewater treatment plant based on previous data. Good results were obtained in the prediction of BOD (biochemical oxygen demand) and SS (suspended solids) through three-layer networks. They concluded that ANNs provide an efficient and robust tool in predicting the plant's performance indicators.

Finally, Dong, Jin & Li (2003) used a neural network to predict low heating values of municipal solid waste from its physical composition. While the lower heating value was considered the output of the network, the weighted percentages of plastic, paper, food, glass and textile were used as inputs to the network due to their strong correlations with lower heating values. The selected feed forward three-layer network showed that the predicted values are more precise than values obtained through a multiple regression model.

### 2.4 Discussion and Conclusions

Many types of variables and methods have been used in the assessment of waste generating factors and waste generation models. Research shows that measurable-objective variables have been analysed, as well as subjective factors such as people's perceptions or their environmental concern. Statistical methods such as multiple regression and time-series analysis have been developed in order to predict waste generation. The conclusions obtained from the analysed variables and the methods used have led to varied and inconclusive results.

Out of a large set of variables, population and income are the most analysed factors affecting waste generation. Population and income have been assessed several times, in different forms, environments and through different methods concluding that population and/or income are the most significant factors of waste generation. Results about the significance of other variables are uncertain and vary depending on the research.

Different methods have been used in predicting waste generation. Some authors have worked with multiple regression analysis. Their results are unsatisfactory not only due to the selected variables and lack of data, but also because regression models cannot learn from new data and do not adapt to new situations. Alternatively, other authors have considered time-series analysis to be more appropriate for predicting waste generation. Better results have been obtained with time-series, though there are limitations like the need for much larger datasets and the use of appropriate initial assumptions. Using sARIMA and non-linear techniques seem to improve results, although these techniques are not simple to use. Similarly techniques such as grey fuzzy dynamic models, which have been developed using very small datasets, and gray theoretical models have also provided good results.

Finally, even though ANNs have not been applied in assessing solid waste generation factors or predicting solid waste generation, they have performed successfully in waste management problems. The main potential of ANNs is the capability of modelling non-linear problems based on an incremental learning process that occurs in each one of the neurons in the network as the data pass through from inputs to the output layer. ANNs are capable of modelling outcomes and adapting to unseen data based on the network's own experience. Furthermore, they can capture temporal effects from time-series data making them capable of predicting future behaviour reliably. The network's architecture is determined through a trial-and-error process which takes some effort in model development. However, the trained neural networks have been shown to have high performance accuracy.

# CHAPTER 3

# STAGE 1: DETERMINING WASTE GENERATING FACTORS

## 3. SELECTION OF VARIABLES

### 3.1 Literature Review

A thorough review of the existing literature on waste management has found no studies identifying waste generating factors in Chile. Research from other countries has provided the base that supports the variables to be assessed in this case study of Chile.

Research from several countries and on different areas of waste management has been used to provide an overall view of waste generating factors from different societies and environments. The assessed studies have included developed countries such as Canada, Germany and the US, and developing countries like China, Ghana or Vietnam. The studied topics were energy and environmental consumption, environmental policies, environmental psychology, landfills, materials recycling, packaging, pricing programmes, recycling programmes, scavengers, solid waste indicators, solid waste generation and waste management.

As mentioned in Chapter 2, different variables have been analysed by several authors. Their conclusions regarding factors affecting waste generation lead to inconclusive results. Table 3.1 shows variables considered by various researchers. It can be seen that population and income are the most analysed variables. Education and household size are also considered often.

Table 3.1: Matrix of Authors versus Variables Selected in their Research

| Authors, Year / Variables | Age Groups | Climate | Consumption | CPI | Culture | Education | Electricity | Employment | GDP | Geography | Household Size | Income | Population | Residency Type | Tipping Fees | Urbanism Level |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Shell & Shupe, 1972) | | X | | | | | | | | | X | X | X | X | | |
| (Grossman et al., 1974) | | | | | X | X | | | | | | X | X | X | | |
| (Ali Khan & Burney, 1989) | | X | X | | X | | | | X | X | X | X | X | | | |
| (Arey et al., 1993) | | X | | | | | | | | X | | X | X | | | |
| (Chang et al., 1993) | | | | X | | | | | | | | X | X | | | |
| (Hong et al., 1993) | | | | | | X | | | | | X | X | | | X | |
| (McBean & Fortin, 1993) | | | | | | | | X | | | X | | X | X | | |
| (Kerzee et al., 1994) | X | | | | | X | | X | | | X | X | X | | | X |
| (Hockett et al., 1995) | | | X | | | | | | | X | | X | X | | X | X |
| (Cailas et al., 1996) | | | | | | X | | X | | | X | | X | | | X |
| (Hamburg et al., 1997) | X | | | | | X | | | | | | | X | | | |
| (Margai, 1997) | X | | | | | X | | X | | | X | X | | X | | X |
| (USEPA, 1997) | | | | X | | | | X | | | | | X | | | |
| (Koushki & Al-Khaleefi, 1998) | X | | X | | | X | | X | | X | X | X | | X | | X |
| (Rachdawong et al., 2000) | | X | X | | | | X | | X | | | | X | | | |
| (Bagby et al., 2001) | | | | | | | | X | | | X | X | X | X | | |
| (Bruvoll, 2001) | | | | | | | | | | | | X | X | | X | |
| (Buenrostro et al., 2001) | X | X | | | | X | | | | | X | X | | | | |
| (Orccosupa et al., 2002) | | X | | | | X | X | | X | | | X | | | | |

### 3.2 Selection Method

Based on the literature review, possible waste generating factors were evaluated and a preliminary set of relevant variables selected.

<u>Variables:</u> While past literature does not lead to any firm conclusion, a set of variables was identified as possible indicators. Population, economic, education, dwelling, geographic and waste-related characteristics are indicators that were analysed at a communal level in Chile. The following is a comprehensive list of the studied variables:

> *Population indicators*: Population (people), Urbanism Level (urban people) and Percentage of Urbanism (% urban people), Population Density (people/km$^2$), Gender and Percentage of Male Population (%), Age Groups (0-14, 15-24, 25-44, 45-64 and 65+ years of age) and Percentage of Native Population (%).

*Economic indicators*: Poverty Level (indigent, poor non-indigent, non-poor people), Monthly Income per Household (USD/month), Regional Economic Activities (trade, mining, agriculture-silviculture, manufacturing), GDP (regional % of total GDP), Foreign Investment (regional % of total foreign investment), Exports (regional % of total exports), Construction Rate ($m^2$), Vehicles (number), Employment Rate (% of employed people), Labour Force (% of active workers) and Unemployment Rate (regional % of total unemployment).

*Education indicators*: Education (years), Cultural Activities (number of public performances), Libraries (number) and Illiteracy Rate (% of illiterate people).

*Dwelling indicators*: Houses (number) and House Density (number of people per household).

*Geographic indicators*: Climate (warm desert, mild and temperate, temperate and rainy, cold steppe) and Geographic Location (coast, mountain, valley).

*Waste-related indicators*: Waste Generation (tonnes/month from 2001), Waste Generation Rate (% of variation between 2002 and 2001), Per Capita Waste Generation (kg/pc/day in 2002), Existence of Disposal Sites (yes/no).

### 3.3 Data Collection

This first part of research was developed in New Zealand. Data for determining global variables was collected through websites of public institutions of Chile.

Many institutions display information through documents and reports on their websites. Data was collected from Central Bank of Chile (www.bcentral.cl), the National Commission for the Environment (www.conama.cl), the National Institute of Statistics (www.ine.cl) and the Ministry of Planning and Cooperation (www.mideplan.cl). Listed below are the sources of data for the indicators.

*Population indicators*: Population, Urbanism Level and Percentage of Urbanism, Gender and Percentage of Male Population (INE, 2003). Population Density (calculated with data from (INE, 2001a) and (INE, 2003)). Age Groups (Instituto Nacional de Estadísticas - INE, 1998a) and Percentage of Native Population (Instituto Nacional de Estadísticas - INE, 1992a).

*Economic indicators*: Poverty Level, Monthly Income per Household and Labour Force (Ministerio de Planificación - MIDEPLAN, 1998). Regional Economic Activities (Banco Central de Chile, 2002b), GDP (Banco Central de Chile, 2003), Foreign Investment (Banco Central de Chile, 2002c), Exports (Ministerio de Planificación - MIDEPLAN, 2002), Construction Rate (Instituto Nacional de Estadísticas - INE, 1998b), Vehicles (Instituto Nacional de Estadísticas - INE, 1999), Employment and Unemployment Rates (Instituto Nacional de Estadísticas - INE, 2002).

*Education indicators*: Years of Education and Illiteracy Rate (MIDEPLAN, 1998), Cultural Activities and Number of Libraries (Instituto Nacional de Estadísticas - INE, 1998c).

*Dwelling indicators*: Number of Houses (INE, 2003) and House Density (calculated with data from (INE, 2001a) and (INE, 2003)).

*Geographic indicators*: Climate (Banco Central de Chile, 2002c) and Geographic Location (Instituto Nacional de Estadísticas - INE, 2001b).

*Waste-related indicators*: Waste Generation (CONAMA, 2003), Waste Generation Rate (calculated with data from (Comisión Nacional del Medio Ambiente - CONAMA, 2002d) and (CONAMA, 2003)), Per Capita Waste Generation (calculated with data from (CONAMA, 2002) and (INE, 2003)), Existence of Disposal Sites (CONAMA, 2003).

A table with all the data per commune is included in Appendix 2.

### 3.4 Data Processing

- Multicollinearity: The level of correlation among all the variables was tested through a pair-wise correlation matrix (Appendix 3).

The multicollinearity analysis showed that Waste Generation (the dependent variable) is highly correlated (>0.70) to Urban Population, Male Population, Population, Non-Poor Population, Number of Houses, Age Groups and Number of Vehicles. These main independent variables are also highly correlated to each other, making it difficult to separate their respective effects on the dependent variable. (Table 3.2)

Table 3.2: Main Independent Variables

| Correlations | Urban † | Males † | Pop † | NP Pop ¢ | Houses † | 0-14 § | 15-24 § | 25-44 § | 45-64 § | 65+ § | Vehicles ¥ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Waste £ | 0.883 | 0.877 | 0.875 | 0.865 | 0.849 | 0.836 | 0.826 | 0.847 | 0.831 | 0.748 | 0.745 |
| Urban Pop | 1.000 | 0.996 | 0.997 | 0.982 | 0.982 | 0.972 | 0.965 | 0.978 | 0.958 | 0.864 | 0.818 |
| Males | X | 1.000 | 0.999 | 0.979 | 0.982 | 0.977 | 0.967 | 0.979 | 0.955 | 0.855 | 0.806 |
| Population | X | X | 1.000 | 0.982 | 0.985 | 0.976 | 0.968 | 0.980 | 0.959 | 0.864 | 0.814 |
| NP Pop | X | X | X | 1.000 | 0.971 | 0.971 | 0.976 | 0.986 | 0.983 | 0.907 | 0.844 |
| Houses | X | X | X | X | 1.000 | 0.951 | 0.953 | 0.964 | 0.955 | 0.892 | 0.848 |
| 0-14 | X | X | X | X | X | 1.000 | 0.989 | 0.993 | 0.963 | 0.846 | 0.758 |
| 15-24 | X | X | X | X | X | X | 1.000 | 0.995 | 0.986 | 0.898 | 0.813 |
| 25-44 | X | X | X | X | X | X | X | 1.000 | 0.984 | 0.888 | 0.812 |
| 45-64 | X | X | X | X | X | X | X | X | 1.000 | 0.948 | 0.864 |
| 65+ | X | X | X | X | X | X | X | X | X | 1.000 | 0.888 |
| Vehicles | X | X | X | X | X | X | X | X | X | X | 1.000 |

† 2002 (INE, 2003)
¢ 1998 (MIDEPLAN, 1998)
§ 1998 (INE, 1998a)
¥ 1999 (INE, 1999)
£ 2002 (CONAMA, 2003)

As the main independent variables are all highly correlated to each other, only one could be included in the model. Several models were run with only one main variable plus secondary variables highly correlated to Waste Generation but with low correlation to the main variable. The selected secondary variables were Percentage of Urban Population, Years of Education, Number of Libraries, Indigent Population and Poor Non-Indigent Population. They were selected because they do not correlate strongly to the main variables. From Table 3.3 it can be seen that the secondary variables correlate higher with any main variable other than waste, making it difficult to select those secondary variables.

Table 3.3: Correlations between Main and Secondary Variables

| Correlations | | Secondary Variables %UrbPop † | Education ¢ | Libraries # | Indigents ¢ | Poor NI ¢ |
|---|---|---|---|---|---|---|
| Main Variables | Waste | 0.502 | 0.519 | 0.522 | 0.503 | 0.691 |
| | Urban | 0.562 | 0.587 | 0.616 | 0.637 | 0.824 |
| | Males | 0.546 | 0.555 | 0.609 | 0.658 | 0.841 |
| | Pop | 0.548 | 0.568 | 0.615 | 0.653 | 0.836 |
| | NP Pop | 0.545 | 0.599 | 0.661 | 0.602 | 0.805 |
| | Houses | 0.548 | 0.589 | 0.682 | 0.603 | 0.802 |
| | 0-14 | 0.534 | 0.52 | 0.561 | 0.69 | 0.886 |
| | 15-24 | 0.547 | 0.564 | 0.634 | 0.654 | 0.859 |
| | 25-44 | 0.543 | 0.564 | 0.627 | 0.646 | 0.852 |
| | 45-64 | 0.56 | 0.614 | 0.7 | 0.6 | 0.815 |
| | 65+ | 0.541 | 0.649 | 0.812 | 0.498 | 0.696 |
| | Vehicles | 0.52 | 0.694 | 0.85 | 0.364 | 0.549 |

† 2002 (INE, 2003)
¢ 1998 (MIDEPLAN, 1998)
# 1998 (INE, 1998c)

- Heteroskedasticity:

  The Breusch and Pagan test[7] detected heteroskedasticity in all the models. Its effect was reduced using the Two-Step Weighted Least Square method[8].

Population (POP) was selected as the main variable because it was part of the best model after heteroskedasticity was reduced. Population had the highest correlation to every other main variable, making it capable of representing them in the explanatory model. The other variables (the secondary) selected in the model were Percentage of Urban Population (PUP), Years of Education (EDU), Number of Libraries (LIB) and Indigent Population (IND). The variable Poor Non-Indigent Population was not included because it correlated highly with the secondary variables. Analysis of Variance of the Breusch and Pagan test (for detecting heteroskedasticity in all the variables) and the Two-Step Weighted Least Square method (for reducing its effect) are included in Appendix 4.

[7] Breusch, T.S., & Pagan, A.R. (1979). A Simple Test for Heteroskedasticity and Random Coefficient Variation. *Econometrica, 47*, 1287-1294.
[8] Prais, S.J., & Houthakker, H.S. (1955). *The Analysis of Family Budgets* (p. 55ff.). New York: Cambridge University Press.

In order to clarify what these five variables mean, here are some definitions:

- Population: the inhabitants of a place ("Oxford Modern English Dictionary", 1996).
- Percentage of Urban Population: the percentage of urban population out of the total population of a place. As defined by Rae (2003, cited in Strange, 2004, p. 1), urban people reside in areas complying with the following features of urbanism: industrial convergence (spatial concentration of manufacturing), dense fabric of enterprise (presence of many small and mutually dependent firms), centralised clustering of housing (fostering the interaction among residents), dense fauna of civic organisations (mediating the interactions among residents), and a pattern of political integration (where the residents are broadly involved in the city's governance).

  In the case of Chile, urban areas are those that possess concentrations of housing with more than 2,000 inhabitants and those that fluctuate between 1,001 and 2,000 inhabitants, where 50% or a greater percentage of the population is economically active. Due to their nature, tourism and recreation centres with more than 250 houses, although not complying with the above population requisite are also considered urban (Instituto Nacional de Estadísticas - INE, 1992b).
- Years of Education: average number of years a person has studied (primary, secondary or tertiary).
- Number of Libraries: number of public and private libraries.
- Indigent Population: number of indigents (in the case of Chile, people are considered indigent if their income is not enough to cover their basic needs (www.mideplan.cl)).

Table 3.4 shows that all the selected explanatory variables correlate relatively highly to Waste Generation (WG) complying with a significant level of correlation required for model development.

Table 3.4: Correlations between Selected Variables

| Correlations | Population | %Urban | Education | Libraries | Indigent |
|---|---|---|---|---|---|
| Waste £ | 0.875 | 0.502 | 0.519 | 0.522 | 0.503 |
| Population | X | 0.548 | 0.568 | 0.615 | 0.653 |
| % Urban | X | X | 0.527 | 0.383 | 0.422 |
| Education | X | X | X | 0.558 | 0.177 |
| Libraries | X | X | X | X | 0.260 |

Table 3.4 also shows that all the secondary variables are more correlated to Population than to Waste, highlighting the importance of Population as the variable that contributes most to Waste Generation. However, Population by itself could not cluster the communes in an appropriate manner to analyse waste generation in Chile. For example, Table 3.5 shows that two communes with similar Population but different levels of Urban Population, Years of Education, Number of Libraries or Indigent Population do not generate similar amounts of waste. This justifies the use of the additional variables.

Table 3.5: Population Figures versus Other Explanatory Variables

| Commune | WG (tonnes/month) | POP (inhabitants) | PUP (%) | EDU (years) | LIB (number) | IND (people) |
|---|---|---|---|---|---|---|
| Juan Fernández | 17.9 | **633** | 94.5 | 9.0 | 0 | 20 |
| Laguna Blanca | 10.0 | **663** | 0.0 | 8.7 | 0 | 0 |
| Guaitecas | 27.2 | **1,539** | 91.7 | 8.3 | 0 | 0 |
| Palena | 16.0 | **1,690** | 0.0 | 9.2 | 1 | 114 |
| María Elena | 300.0 | **7,530** | 98.4 | 9.3 | 2 | 210 |
| San Pedro | 27.2 | **7,549** | 0.0 | 6.7 | 1 | 447 |
| Graneros | 715.3 | **25,961** | 87.3 | 8.6 | 1 | 2,022 |
| Carahue | 450.0 | **25,696** | 45.1 | 6.2 | 2 | 4,444 |
| Padre Las Casas | 1,312.4 | **58,795** | 57.3 | 8.1 | 4 | 10,388 |
| Talagante | 2,057.9 | **59,805** | 83.5 | 9.2 | 16 | 2,882 |
| Ñuñoa | 5,625.1 | **163,511** | 100.0 | 13.4 | 62 | 7,710 |
| Los Ángeles | 1,126.9 | **166,556** | 74.1 | 9.1 | 27 | 3,360 |

### 3.5 Results

Relationships Establishment: After the heteroskedasticity problem was reduced, Multi Layer Perceptron (MLP) neural networks were used to determine the relationship between Waste and the selected generating factors and their relative contribution to Waste Generation. In order to maintain the values of the variables to one-digit figures, these were transformed as follows: Log(Population) = LOG(POP); $(\text{Libraries})^{1/3}$ = CURT(LIB); $(\text{Indigent})^{1/5}$ = FP(IND); $(\text{Education})^{1/2}$ = SQRT(EDU), and $(\text{Waste})^{1/5}$ = FP(WG). PUP is in the range from 0 to 1.

The dataset (342 data points) was divided into three sets: 90% for training, 5% for testing and 5% for validation. A three layer MLP neural network was capable of modelling the relationship between the five explanatory variables and Waste Generation. Based on the validation dataset, the network modelled the relationship with $R^2 = 0.819$ and a correlation coefficient between the real and predicted outputs of 0.915. The architecture of the MLP had five input neurons, twenty hidden neurons and one output neuron. The input neurons used a linear function and both hidden and output neurons used logistic functions. The three layers were trained with a learning rate of 0.1, momentum = 0.1 and initial weight equal to 0.3. The input vectors were selected randomly to be presented to the network and weights were updated using backpropagation learning. In neural network training, inputs are repeatedly presented to the network and processing of the whole dataset once is called an epoch. Usually, it requires several to many epochs for completing the training. Because, neural networks have a lot of flexibility, they can memorise (overfit) the data by going beyond the state of generalisation. In order to prevent this a test dataset is processed intermittently during training, and in this analysis the MSE on the test data was obtained by passing the test dataset through the network after each presentation of 200 input vectors (interval) to the network. The network was trained until MSE on test data did not change for 20,000 iterations of test data. The network was trained after 248,400 learning epochs. Figure 3.1 shows actual waste generation superimposed on the network outputs for all 342 communes (whole dataset). It illustrates that actual and predicted amount of waste agree remarkably well ($R^2$ = 0.861) with each other demonstrating the effectiveness of the model.

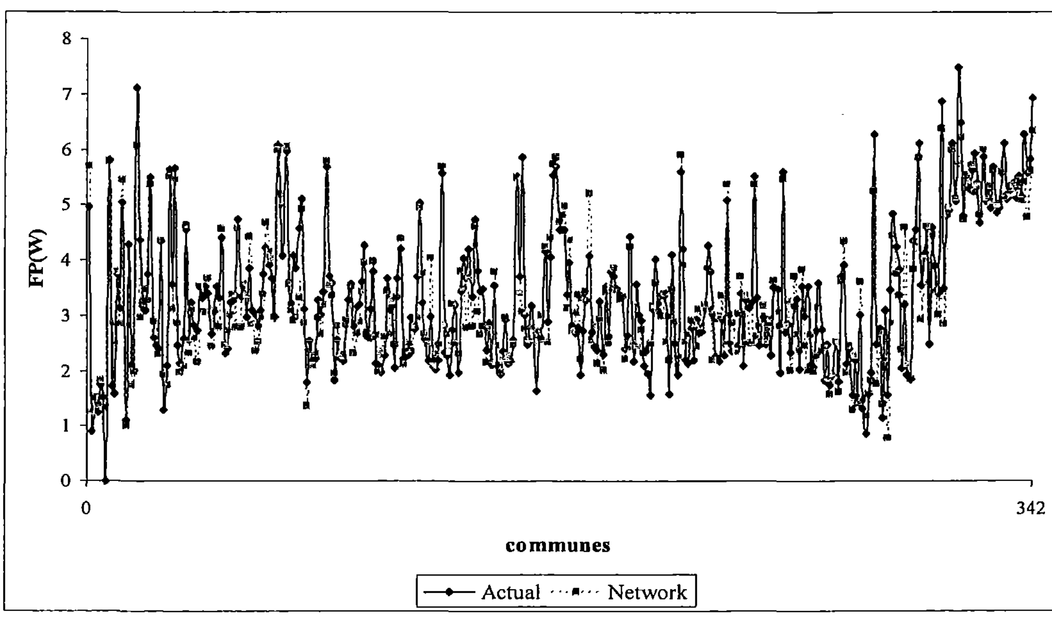



Figure 3.1: Actual Waste Generation superimposed on MLP Neural Network Outputs for the 342 Communes of Chile (Whole Dataset)

Figure 3.2 shows the correlation between the actual and predicted waste. The figure presents the linear equation between actual (abscissa) and the network output (ordinate), and the coefficient of multiple determination $R^2$ for the whole dataset.

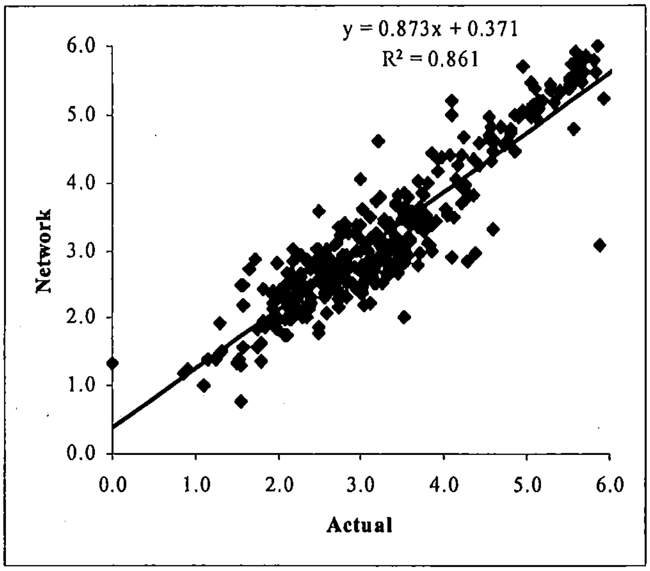



Figure 3.2: Actual Outputs versus Network Outputs (Whole Dataset)

Figure 3.3 shows the predicted output superimposed on the actual waste for each of the communes in the validation set. It indicates that there is a good agreement between the two variables as confirmed by correlation plot of predicted and actual waste (Figure 3.4) ($R^2 = 0.819$).

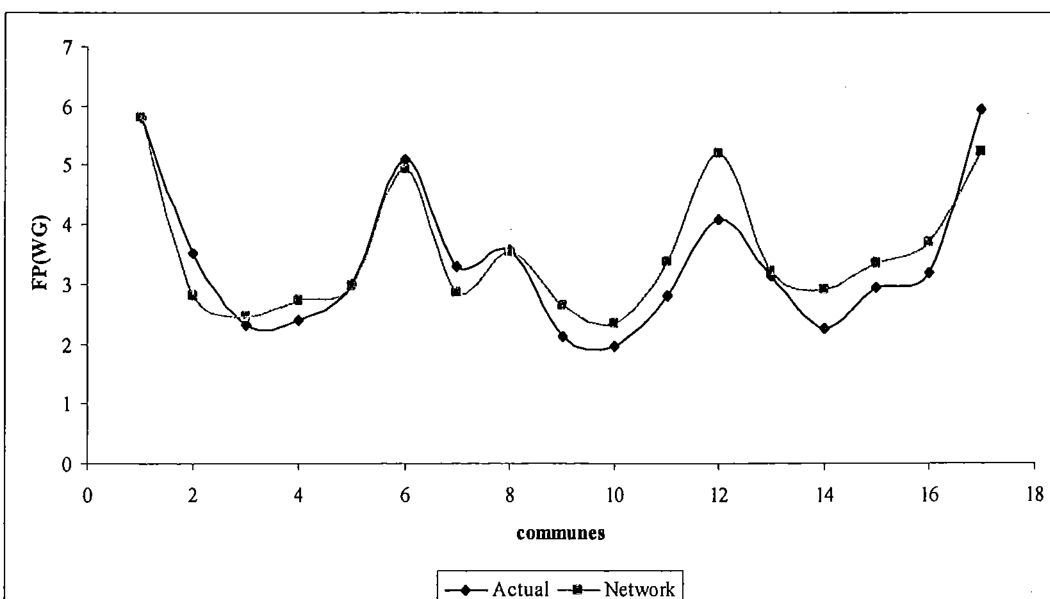



Figure 3.3: Actual Waste Generation superimposed on MLP Neural Network Outputs for the 17 Communes on the Validation Dataset

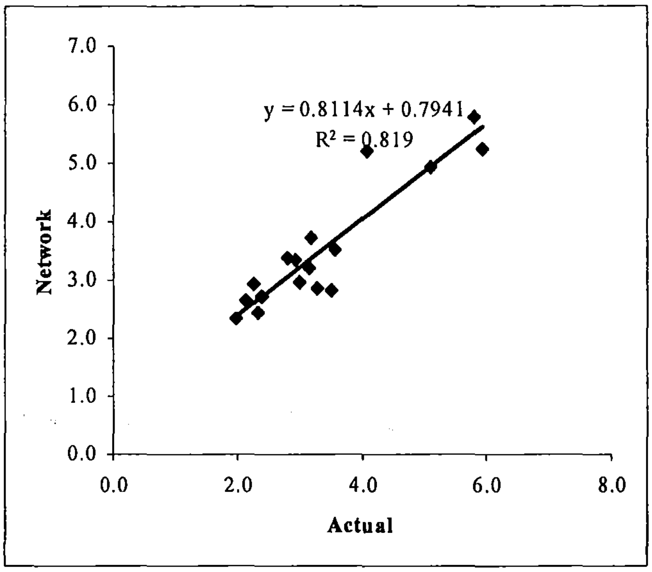



Figure 3.4: Actual Outputs versus Network Outputs (Validation Dataset)

Network output on the validation set demonstrates how well the network performs on unseen data and is a test of its validity. These results clearly demonstrate that the developed neural network generalises well with great accuracy on unseen data and is a reliable model for predicting waste. Appendix 5 shows plots of the training set average errors versus the epochs elapsed and the testing set average error versus the intervals elapsed.

The trained network was further analysed to ascertain the contribution of each explanatory variable. Population is the variable that contributes most to Waste Generation (41.3%), followed by Number of Libraries (16.9%), Indigents (15.4%), Percentage of Urban Population (13.8%) and Years of Education (12.5%) as shown in Figure 3.5.

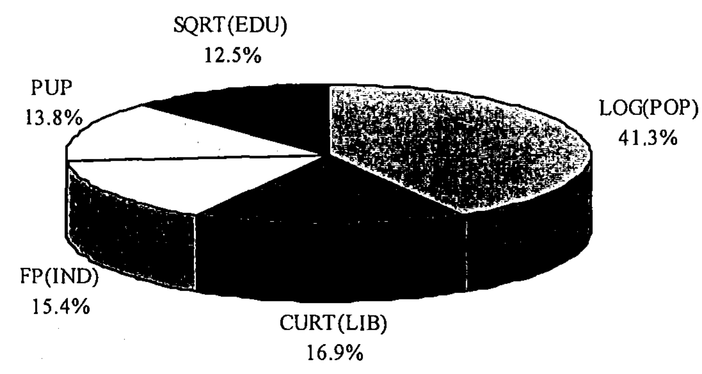



Figure 3.5: Relative Contribution of Every Explanatory Variable in Modelling Waste Generation

All the variables contribute positively to Waste Generation. Appendix 6 shows 3D plots of all the variables against WG. An increase of 1,000 people (2.3% of average population) will result in an increase in waste generation between 28.4 and 32.5 tonnes/month (934 and 1,069 kg/day). Increasing urban population by 1% (1.6% of average percentage of urban population) will raise waste generation between 11 and 30 tonnes/month (362 and 986 kg/day). If the number of years of education increases by one year (11.5% of average years of education), the level of waste will be between 83.6 and 209.0 tonnes/month higher (2,748 and 6,871 kg/day). The addition of one library (17.4% of average number of libraries) will increase waste between 1.1 and 5.7 a month (38 to 189 kg/day). One hundred more indigents to a commune (4.7% of average number of indigents) will increase waste generation between 0 and 1.1 tonnes/month (0 and 36.1 kg/day).

The 3D plots in Appendix 6 show that inputs are nonlinearly related to waste and that nonlinearity is more pronounced for Population. Some of these variables, such as Number of Libraries and Years of Education do not directly influence waste, but they represent the socio-economic conditions reflecting people's propensity to affect waste generation.

### 3.6 Multiple Linear Regression Analysis

Traditionally, Multiple Linear Regression Analysis (MLR) models have been used in modelling relationships between independent explanatory variables and dependent explained variables. A MLR model was run to compare its results with the ones obtained using ANNs. The dataset was transformed to a range of values between 0 and 1 for all the variables.

Initially the MLR model suffered heteroskedasticity ($R^2 = 0.777$) and this effect was reduced using the Two-Step Weighted Least Square method. After reducing the heteroskedasticity effect, the MLR model result is the following:

$$WG' = -\underset{(0.009)^{9}}{0.018} + \underset{(0.052)}{0.647} * POP' + \underset{(0.004)}{0.00004} * PUP' + \underset{(0.015)}{0.027} * EDU' + \underset{(0.065)}{0.032} * LIB' - \underset{(0.014)}{0.042} * IND' \qquad R^2 = 0.615$$

The MLR model is less representative than the model obtained with the MLP ($R^2 = 0.861$). The equation shows that among the five explanatory variables, Population is largely the most important variable contributing to Waste Generation, followed by Indigent Population, Number of Libraries and Years of Education. According to the parameters obtained from the MLR, Percentage of Urban Population has almost no influence on Waste Generation. A significant result from this model is that the intercept coefficient is very small, confirming the significance of the five factors explaining Waste Generation. Appendix 7 shows results from the ANOVA. As shown already, 3D plots in Appendix 6 show that most variables are indeed nonlinearly related to waste, an attribute not captured by MLR.

### 3.7 Discussion and Conclusions

The aim of this chapter is to understand waste generating variables in order to recognise the factors that contribute to waste generation in Chile. This chapter shows the process of identifying and selecting waste generating factors by methods of multicollinearity and heteroskedasticity analysis. It also tests the factors' capacity to model waste generation using ANNs and determines how these factors contribute to waste generation in Chile.

Based on the literature review, a list of variables was considered for analysis. Variables were grouped according to its Population, Economic, Education, Dwelling, Geographic and Waste-related characteristics.

[9] Standard errors are in parentheses.

A multicollinearity analysis showed that there were two groups of variables, those highly correlated (>0.70) to Waste Generation and to each other (main variables) and those less correlated to waste and to each other (secondary variables). Population, Urban Population, Male Population, Non-Poor Population, Number of Houses, Age Groups and Number of Vehicles form the main variables. Only one of these was selected because the high correlation among them makes it difficult to separate their influence on Waste Generation. The second group consisted of the secondary variables: Percentage of Urban Population, Years of Education, Number of Libraries, Indigent Population and Poor Non-Indigent Population. These variables were selected because they do not correlate as strongly to any of the main variables and to each other but still showed significant correlation to waste.

Several models were run using one main variable and all the secondary variables. Using the Breusch and Pagan test, heteroskedasticity was detected in all the models. This problem was reduced through a Two-Step Weighted Least Square method with Population as the main variable and Percentage of Urban Population, Years of Education, Number of Libraries and Indigent Population as secondary variables. Even though all the secondary variables correlate higher to Population than to Waste Generation, Population itself is not able to characterise waste generating communes. Communes with similar Population and different levels of Urban Population, Years of Education, Number of Libraries and Indigents do not generate similar amounts of waste.

The capacity of the selected model to represent Waste Generation was tested using a three-layer Multi Layer Perceptron neural network. This model was capable of representing Waste Generation with $R^2 = 0.819$ on the validation dataset. Results showed that Population is the most important variable contributing to Waste Generation (41.3%), followed by Number of Libraries (16.9%), Indigent Population (15.4%), Percentage of Urban Population (13.8%) and Years of Education (12.5%). All the variables contribute positively to Waste Generation, i.e., an increase in any of them will increase waste generation levels, and most are nonlinearly related to waste generation. The non-linearity is more pronounced for Population. As mentioned in Section 1.3, only disposed waste has been considered in this model, not recycled waste.

Despite the limited information available, the analysis presented in this Chapter has shown important results concerning the assessment of waste generating factors in Chile. Similar to other international studies, Population is the most important variable contributing to Waste Generation in Chile. Statistical analyses showed that Population is more important than any other of the assessed variables and that it is correlated to all the other variables. However, the data analyses showed that Population was not capable of modelling Waste Generation by itself and that other factors needed to be considered.

When Population is combined with Percentage of Urban Population, the level of contribution of population indicators increases to more than 55%. This demonstrates that this link is essential to establish adequate relationships between people and their waste generation rate. Results also show that educational factors (Number of Libraries and Years of Education) are the second most important group contributing almost 30% to Waste Generation. This confirms education as fundamental in contributing to waste through improved access to services and goods but educated citizens could be relatively easily converted to individuals committed to protecting the environment.

Finally, the variable Indigent People, although the least important among the variables, does contribute a significant 15% to Waste Generation. Understanding why this variable is important to waste generation for the case of Chile is not as straightforward as with the other variables and several reasons need to be analysed. Firstly, people with a low level of income in Chile, either indigents or poor non-indigents, have access to education of lower quality. Such poor education also means poor environmental education, which is also transformed into low level of environmental concern. This is because there are several other day-to-day issues that may be more pressing or urgent. Secondly, low-income Municipalities (where most indigents live) focus their limited resources on primary services such as education and health, leaving environmental issues as secondary activities. Thirdly, in low-income communes in Chile, there are much fewer recycling campaigns than in higher-income communes, which may help to reduce waste generation and create environmental awareness among the population (Orccosupa et al., 2002). Finally, the Environmental Kuznets Curve theory shows that pressure on the environment (waste generation, level of concentration of pollution or flow of emissions, depletion of resources, etc.) "increases faster than income in the early stage of development and slows down relative to economic growth in higher income levels". As can be seen from Figure

3.6, in the first stage of development (<*a*), environmental degradation grows rapidly because high priority is given to increasing material output, and people are more interested in jobs and income than in the environment. This growth results in greater exploitation of natural resources and emission of pollutants, putting more pressure on environment. "People are too poor to pay for abatement, and/or disregard environmental consequences of growth. In later stage of development (*b*<), as income rises, people value the environment more, regulatory institutions become more effective and pollution level declines" (Dinda, 2004).

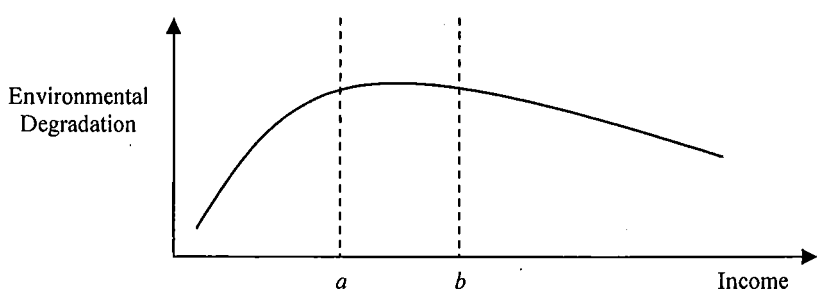



Figure 3.6: Environmental Kuznets Curve

Chile, as a middle-income country, is located around *a*. A portion of the population has income equivalent to the flat part of the curve; however, indigents and poor non-indigents are on the increasing side of the curve which may help to understand the contribution of poor people to waste generation in the case of Chile. As described by the theory, this group of people are more interested in finding a stable job and increasing their quality of life than in taking care of the environment, which is transformed in a reasonable indifference towards waste minimisation.

Finally, it is necessary to note that other important factors mentioned in the literature such as the existence of tipping fees, consumption levels, households size or residency type were not possible to be assessed because the information was not available. Future research should focus on a wider variety of factors which may further explain waste generation.

# CHAPTER 4

# STAGE 2: CLUSTERING OF COMMUNES AND SELECTION OF REPRESENTATIVE COMMUNES

## 4.1 Clustering of Communes

### *4.1.1 Self-Organising Feature Maps*

A Self-Organising Feature Map (SOFM) is a type of competitive learning network that preserves spatial neighbourhoods for each output neuron based on a property of topology preservation. SOFMs are capable of transforming complex, non-linear statistical relationships between high-dimensional input patterns onto a low-dimensional discrete map by preserving the most important topological characteristics of the data (Kohonen, 1998).

In SOFM, common input neurons are linked to output neurons arranged in a one or two-dimensional grid. This has been previously shown in Figure 2.1(b). As SOFM are unsupervised networks, the inputs are presented without specifying the desired output. After enough inputs have been presented to the network, weights organise the data in such a way that the topologically close neurons become sensitive to similar inputs. Then, outputs are clustered in a natural manner (Lippmann, 1988).

SOFM have been successfully used for projection of multivariate data, density approximation and clustering in different areas such as speech recognition, image processing, robotics and process control.

### *4.1.2 Method*

As explained in Chapter 1 – Research Method, the 342 communes of Chile are clustered with the aim of grouping different types of waste generating communes. From each group, representative communes are selected for detailed analysis.

Results from Stage 1 show that Population, Percentage of Urban Population, Number of Libraries, Years of Education and Indigent Population are the most important variables contributing to waste generation. Based on these variables, communes are clustered according to their waste generation characteristics.

The network has been set to organise three groups. This number of groups was selected because a lesser number would have mixed communes with different characteristics. More than three groups would have required a longer period of analysis and more resources to develop the on-site research.

The data from the 342 communes and the five relevant variables were presented to the network. The dataset was divided into three sets: training, testing and validation. The architecture of the SOFM had five input neurons in the input layer and three output neurons in the output layer. The network was trained at a learning rate of 0.5, initial weight equal to 0.5, number of neighbourhoods set to 2 and number of epochs to 50. The distance measure used to assign an input to a winning output neuron was Euclidean distance. Appendix 8 shows the features of the network, a plot of the distribution per category and a table with the final weights.

#### *4.1.3 Results*

The SOFM neural network clustered the communes into three groups. Group 1 (G1) with 91, Group 2 (G2) with 156 and Group 3 (G3) with 95 communes.

The three groups can be seen in the bi-dimensional plot of the 342 communes shown in Figure 4.1. The plot depicts the Population weighted by its relative contribution (obtained from the neural network in Stage 1) along the abscissa against the weighted sum of the other four explanatory variables. From the plot it can be seen that the network is capable of recognising adequately three types of waste generating communes. G1 clusters communes with relatively small population, mainly rural, with lesser years of education, number of libraries and indigents; G3 clusters communes with larger population, mostly urban, with higher number of years of education, number of libraries and indigents; and G2 clusters communes in the middle range between those in G1 and G3. Appendix 9 shows the communes in each group along with their respective values for the five variables used to cluster them. Figure 4.1 also shows that there is a large spread in these groups between minimum and maximum values (Appendix 10).

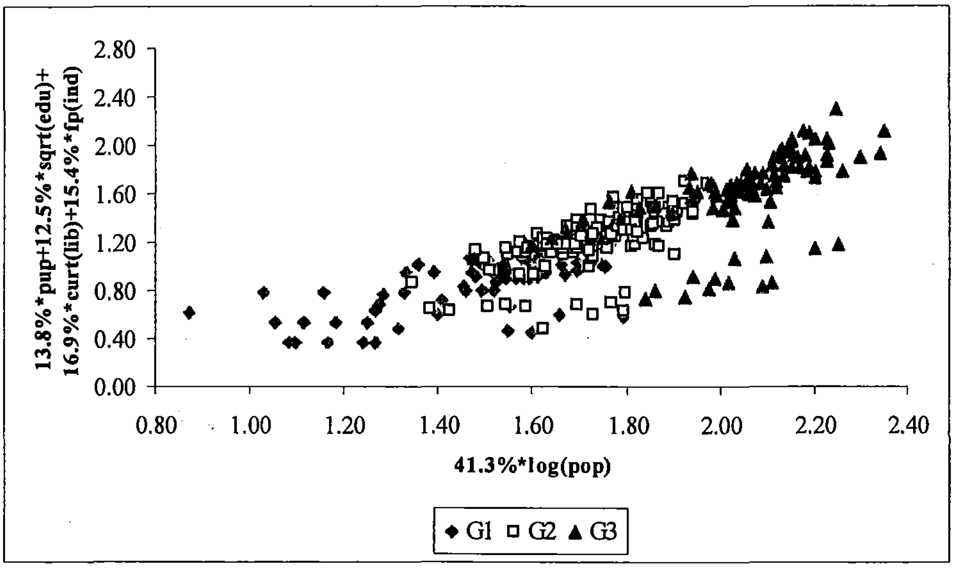



Figure 4.1: Clusters of Communes

Data in Table 4.1 confirms that the three groups have been clustered successfully based on the selected variables. Data from the table validates groups' features mentioned in the previous paragraph. It also shows that in terms of waste generation the groups have also been well clustered (G1 mean = 104.3 tonnes/month; G2 mean = 409.3 tonnes/month; G3 mean = 4,142 tonnes/month). Appendix 11 shows normalised plots of frequency distributions per group and variable.

Table 4.1: Mean and Standard Deviation per Group and Variable

| | WG (tonnes/month) | | POP (people) | | PUP (%) | | EDU (years) | | LIB (number) | | IND (people) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | MEAN | STDEV | MEAN | STDEV | MEAN | STDEV | MEAN | STDEV | MEAN | STDEV | MEAN | STDEV |
| G1 | 104.3 | 141.8 | 6,907.0 | 5,036.8 | 25.3 | 22.1 | 8.2 | 1.0 | 0.8 | 0.9 | 423.3 | 383.9 |
| G2 | 409.3 | 625.4 | 19,312.3 | 11,438.6 | 60.9 | 16.6 | 8.3 | 0.7 | 2.0 | 1.5 | 1,597.1 | 1,611.4 |
| G3 | 4,142.0 | 3,968.7 | 120,791.4 | 91,951.2 | 94.8 | 6.9 | 10.0 | 1.3 | 16.6 | 22.6 | 4,554.3 | 4,693.8 |

### *4.1.4 Discussion and Conclusions*

From the results it can be concluded that the 342 communes of Chile have been successfully clustered into three distinct groups based on the relevant variables from Stage 1. Moreover, once the groups are separately analysed, the level of waste generation from any of the groups corresponds to very well defined intervals. This confirms the good quality of the variables in terms of their relevance to waste generation.

The purpose of clustering the communes is to select a representative commune from each group so that predictive models can be developed. Estimates from these models can be used to obtain an overall estimate for the whole country. A representative commune is one that is able to represent most number of communes in a group. This approach is useful in finding representative communes and making decisions in many other areas related to waste management. For instance, a recycling programme that has been successful in a certain commune may be applied to other communes from the same group because their waste generation factors are similar.

Due to the communes' heterogeneity, it may be interesting to cluster them, in the future, into a larger number of groups to analyse their capacity to represent different types of waste generating communes.

## 4.2 Selection of Representative Communes and Data Collection

### *4.2.1 Method of Selection*

As mentioned in Chapter 1, a representative commune for each group needs to be selected to develop further research. The analyses and conclusions drawn from this study can be extrapolated to the represented communes of each group.

Representative communes are those that, based on the variables found to be relevant for waste generation in Stage 1 (Population, Percentage of Urban Population, Years of Education, Number of Libraries, Indigent Population), represent a significant number of communes from their respective groups. Ideally, representative communes are the source of data collection for forecasting models. For the purpose of this research, a representative commune must comply with the following conditions:

i. Represent the largest number of communes from its group within a ±15% range of $\alpha$ and $\beta$ (weighted value of Population and linear sum of the other four explanatory variables weighted by their relative contribution to waste generation as determined in Stage 1)

$$\alpha \equiv 41.3\% * \frac{\log(POP)}{\max(\log(POP))}$$

$$\beta \equiv 13.8\% PUP + 12.5\% * \frac{\sqrt{EDU}}{\max(\sqrt{EDU})} + 16.9\% * \frac{\sqrt[3]{LIB}}{\max(\sqrt[3]{LIB})} + 15.4\% * \frac{\sqrt[5]{IND}}{\max(\sqrt[5]{IND})}$$

ii. Provide historical data on waste generation levels which is relevant for the purpose of forecasting waste generation for the whole group it represents.

The process of selecting representative communes begins by assessing an initial commune and determining its range of coverage of the communes of its group within a ±15% range of the values of the selected explanatory variables. Then, the coverage range of this first commune is saved and its capacity for providing historical data on waste generation is assessed. If the assessed commune has historical data on waste generation, this commune is saved as the representative commune (otherwise this commune is not considered and the process restarts). Then a new commune is assessed. The coverage range of the new commune is determined and compared with the one that was previously saved. The coverage range of the new commune is saved if this is greater than that of the first commune; otherwise the first one remains saved. The process continues until all the communes have entered into the system. Finally, the commune selected as representative commune is the one with the largest coverage range and able to provide historical data on waste generation.

The following algorithm and Figure 4.2 show the process for selecting representative communes:

$C$: Coverage Range

$RC$: Representative Commune

$n = 0$

Step 0: Is there a commune available for analysis?

If Yes, Go to Step 1

If No, Go to Step 6

Step 1: Input the commune to the system

$n = n + 1$

Step 2: Calculate the coverage range of the commune within a ±15% of α and save it on $C$

If $n = 1$, $C_0 = C$ and $RC$ = input,

Back to Step 0;

If $n > 1$, Go to Step 3

Step 3: Is $C > C_0$?

If Yes, Go to Step 4

If No, Back to Step 0

Step 4: Is the commune able to provide records with historical data on waste generation levels?

If Yes, $C_0 = C$ and $RC$ = last inputted commune

Back to Step 0;

If No, Back to Step 0

Step 5: Representative Commune = $RC$

Step 6: End.

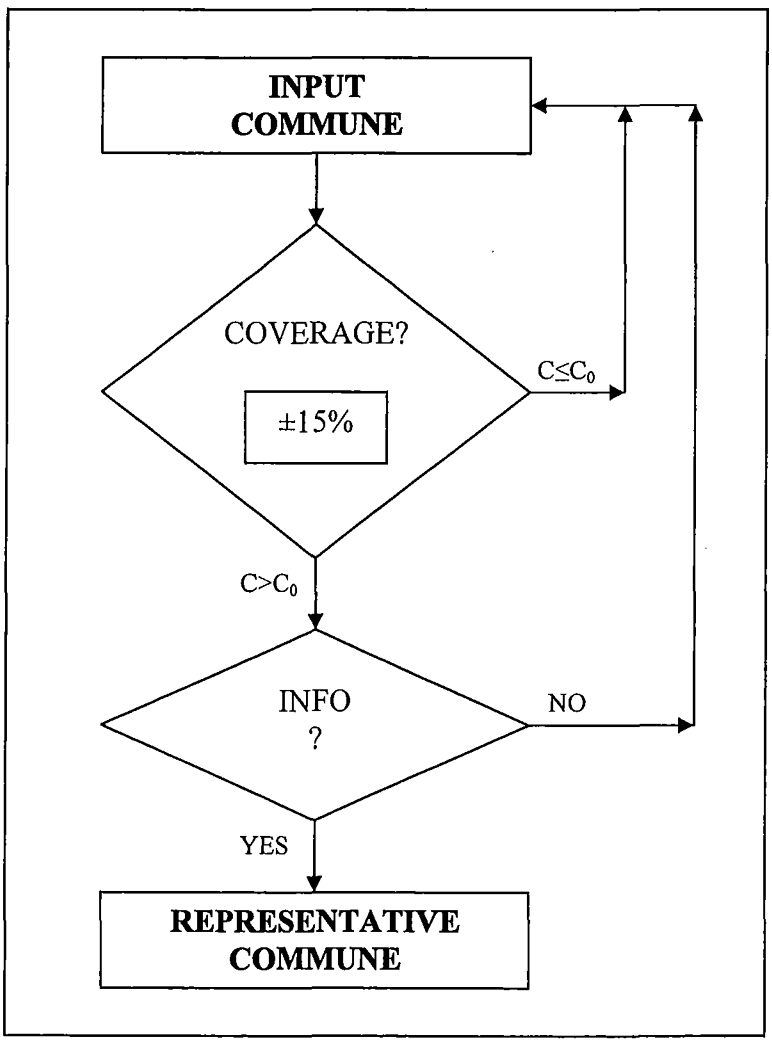



Figure 4.2: Process for Selecting Representative Communes

In the best possible scenario, a representative commune would cover all the communes from its group and would have available records on the required information. Thus the selected communes would cover 100% of the communes of the country. A good scenario would be selecting communes covering between 50% and 75% of all the communes from its group. A satisfactory scenario would cover 25% to 50% and a poor scenario would have less than 25% coverage. All scenarios are subject to data availability.

### *4.2.2 Determining Groups' Representative Communes*

#### 4.2.2.1 Coverage Range

A range of ±15% of the values of the selected explanatory variables has been set to determine the coverage range of the representative communes. The values of the selected explanatory variables of every represented commune must be within ±15% range of those of the representative commune to be represented. Under this criterion, the most representative communes per group are: Group 1: *Marchihue*, *Cobquecura*, *Paredones*, *Ninhue* and *Ránquil*; Group 2: *Olmué*, *Pichilemu*, *Santa Juana* and *Lanco* and Group 3: *Coronel*. However, these communes do not represent 100% of the communes of the country due to dispersion in the value of the explanatory variables.

Table 4.2 shows the best possible scenario for the case of Chile. The most representative communes of every group represent 40 of the 91 communes in Group 1 (44%), 117 of the 156 communes in Group 2 (75%) and 73 of the 95 communes in Group 3 (76.8%), reaching 230 communes within ±15% coverage range of the explanatory variables (67.3% of the total communes). Appendix 12 shows the level of representativeness of every commune per group and plots of the communes represented by the most representative communes.

Table 4.2: Values of Variables for the Most Representative Communes of Every Group and Percentage of Communes in Every Group covered within ±15% Coverage Range of the Representative

| | Rep Commune | WG (tonnes/month) | POP (people) | PUP (%) | EDU (years) | LIB (number) | IND (people) | Representativeness (±15% Range) |
|---|---|---|---|---|---|---|---|---|
| G1 | Marchihue | 55.0 | 6,904 | 32.0 | 8.3 | 1 | 365 | 44.0% |
| G1 | *Cobquecura* | 74.8 | 5,687 | 26.3 | 8.8 | 1 | 439 | 44.0% |
| G1 | *Paredones* | 48.0 | 6,695 | 32.8 | 8.3 | 1 | 353 | 44.0% |
| G1 | *Ninhue* | 41.3 | 5,738 | 25.0 | 8.8 | 1 | 443 | 44.0% |
| G1 | *Ránquil* | 47.5 | 5,683 | 23.5 | 8.8 | 1 | 438 | 44.0% |
| G2 | *Olmué* | 236.4 | 14,105 | 73.6 | 8.5 | 1 | 868 | 75.0% |
| G2 | *Pichilemu* | 110.0 | 12,392 | 76.3 | 7.8 | 1 | 988 | 75.0% |
| G2 | *Santa Juana* | 179.7 | 12,713 | 55.8 | 8.8 | 2 | 981 | 75.0% |
| G2 | *Lanco* | 104.9 | 15,107 | 68.7 | 9.2 | 1 | 1,015 | 75.0% |
| G3 | *Coronel* | 1,949.0 | 95,528 | 95.8 | 9.6 | 4 | 12,003 | 76.8% |

Table 4.2 shows that while Groups 1 and 2 both have several best representatives communes at the same level of representativeness (44% and 75%, respectively), Group 3 has only one commune covering 76.8%.

#### 4.2.2.2 Data Availability and Collection

Once the representative communes were selected from the analysis, a local visit to Chile was required. The purpose of the visit was to obtain historical data for these selected communes. *Comisión Nacional del Medio Ambiente (CONAMA)* and other agencies could only provide limited records on waste generation per commune for 2001 and 2002. To reduce the problem of lack of available data, suitable secondary communes were selected using the same criterion shown in Figure 4.2.

For instance, the selected communes from Group 1 (Table 4.2) did not have enough information or could not be contacted. Instead, more adequate data was collected from the Municipality of *María Pinto*. In addition, figures available from *Pichidegua* provided a good complement to *María Pinto's* data (Ministerio de Planificación - MIDEPLAN & Banco Interamericano de Desarrollo - BID, 1999) (Table 4.3).

Similarly, insufficient information was available in the designated communes from Group 2 (Table 4.2). Therefore, better waste generation figures were obtained from the Municipalities of *Peumo* and *Purén* (Ministerio de Planificación - MIDEPLAN, Banco Interamericano de Desarrollo - BID, KNIGHT PIESOLD S.A. Ingenieros Consultores, &

Voight-Weber Ingenieros, 1997)). In addition, data from *Puerto Aysén* and *Puerto Natales* was collected (Ministerio de Planificación - MIDEPLAN & Banco Interamericano de Desarrollo - BID, 1999) (Table 4.3).

No enough information was available from the selected commune from Group 3 (Table 4.2). Instead data on waste generation from *San Ramón* was collected (Servicio de Salud Metropolitano del Ambiente - SESMA, personal communication, January 29, 2004; Velásquez, 2001) (Table 4.3).

Table 4.3: Values of Variables for the Communes of Every Group where Data on Waste Generation was readily available, Percentage of Communes in Every Group covered within ±15% Coverage Range and Percentage of Data Availability

| | Rep Commune | WG (tonnes/month) | POP (people) | PUP (%) | EDU (years) | LIB (number) | IND (people) | Representativeness (±15% Range) | Data Availability |
|---|---|---|---|---|---|---|---|---|---|
| G1 | María Pinto | 37.2 | 10,343 | 16.0 | 7.5 | 1 | 813 | 40.7% | 94.4% |
| G1 | *Pichidegua* | 182.0 | 17,756 | 28.0 | 8.3 | 0 | 937 | 26.4% | 5.6% |
| G2 | *Puerto Aysén* | 700.0 | 22,353 | 87.6 | 7.8 | 6 | 0 | 69.9% | 13.3% |
| G2 | *Purén* | 208.0 | 12,868 | 54.4 | 7.8 | 1 | 1,373 | 67.3% | 50.0% |
| G2 | *Peumo* | 384.2 | 13,948 | 54.7 | 8.3 | 1 | 736 | 59.0% | 25.0% |
| G2 | *Puerto Natales* | 250.0 | 19,116 | 88.8 | 8.4 | 2 | 0 | 49.4% | 11.1% |
| G3 | *San Ramón* | 2,949.6 | 94,906 | 100.0 | 9.0 | 9 | 3,658 | 74.7% | 100.0% |

It is necessary to clarify that the selection process was developed in New Zealand just with a small amount of data provided by *CONAMA* via email. This data just gave a partial view of the capacity of some communes to provide historical data on waste generation. Later, during the fieldwork developed in Chile, it was realised that the initially selected communes did not have enough historical data and then secondary communes were selected.

#### 4.2.2.3 Data Analysis

Table 4.4 shows that when using the communes where data has been readily available, the real coverage range decreased to 39.6% for Group 1 (36 communes), 38.5% for Group 2 (60 communes) and 74.7% for Group 3 (71 communes). This resulted in a decrease in the total number of communes covered from 67.3% to 48.8%, i.e., from 230 to 167 communes. Appendix 13 shows the calculations to reach the above figures, the list of communes included in every group and plots of the communes represented by the secondary representative communes.

Table 4.4: Calculations to determine the Final Number of Communes Represented by the Representative Communes

| | Representative Commune | (A) Total Number of Communes | (B) Representativeness (±15% Range) | (C = A x B) Represented Communes | (D) Data Availability | (E = C x D)* | Final Communes Represented |
|---|---|---|---|---|---|---|---|
| G1 | María Pinto | 91 | 40.7% | 37 | 94.4% | 35 | 36 |
| | *Pichidegua* | | 26.4% | 24 | 5.6% | 1 | |
| G2 | *Puerto Aysén* | 156 | 69.9% | 109 | 13.3% | 15 | 60 |
| | *Purén* | | 67.3% | 105 | 50.0% | 52 | |
| | *Peumo* | | 59.0% | 92 | 25.0% | 23 | |
| | *Puerto Natales* | | 49.4% | 77 | 11.1% | 9 | |
| G3 | *San Ramón* | 95 | 74.7% | 71 | 100.0% | 71 | 71 |

* See details of calculation in Appendix 13

As the coverage of each group has been modified to a lesser number of communes, the parameters shown in Table 4.1 have also changed and updated values are shown in Table 4.5.

Table 4.5: Mean and Standard Deviation per Group and Variable as determined by the Represented Communes

| | WG (tonnes/month) | | POP (people) | | PUP (%) | | EDU (years) | | LIB (number) | | IND (people) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | MEAN | STDEV | MEAN | STDEV | MEAN | STDEV | MEAN | STDEV | MEAN | STDEV | MEAN | STDEV |
| G1 | 106.4 | 136.0 | 8,715.9 | 4,229.6 | 27.6 | 13.3 | 8.3 | 0.9 | 1.1 | 0.5 | 608.2 | 388.5 |
| G2 | 266.2 | 200.5 | 16,129.2 | 6,220.4 | 53.1 | 14.9 | 8.2 | 0.8 | 1.5 | 0.9 | 1,185.9 | 931.3 |
| G3 | 4,355.8 | 4,033.7 | 127,239.4 | 82,732.0 | 94.7 | 7.6 | 9.9 | 1.2 | 14.7 | 14.5 | 5,195.3 | 4,262.8 |

Appendix 14 shows normalised plots of frequency distributions per group and variable as determined by the represented communes.

#### 4.2.2.4 Results

The most representative communes of each group could not be used for representing the other communes of their respective groups due to a lack of available data. Despite this problem, the selected secondary communes represented almost half of the communes of Chile. Table 4.6 shows that using the secondary communes the model has represented 40.8% of the waste generated in communes from Group 1, 25.0% from Group 2 and 78.6% from Group 3. As a consequence further forecasting of waste generation can be applied to a significant portion (70.5%) of the waste generated in Chile. Furthermore, the model has been capable of representing the waste generated by a total of 10,315,523 people (68.2%). This is important, as this represents the potential benefits from the use of this model.

Table 4.6: Represented and Total Levels of Population and Waste Generated per Group and at a Country Level

| | | Represented | Total | % |
|---|---|---|---|---|
| | G1 | 3,898 | 9,559 | 40.8 |
| WG¢ | G2 | 15,969 | 63,843 | 25.0 |
| (tonnes/month) | G3 | 309,142 | 393,366 | 78.6 |
| | Total | 329,009 | 466,769 | 70.5 |
| | G1 | 313,773 | 628,538 | 49.9 |
| POP¢ | G2 | 967,750 | 3,012,711 | 32.1 |
| (people) | G3 | 9,034,000 | 11,475,186 | 78.7 |
| | Total | 10,315,523 | 15,116,435 | 68.2 |

¢: 2002 figures

#### 4.2.2.5 Discussion and Conclusions

The aim of Chapter 4 was to select adequate representative communes based on the relevant waste generation variables. These representative communes represent most of the communes from their respective groups and provide relevant information for further forecasting of waste generation.

Using the first part of the criteria for selecting representative communes (largest representation of communes), five communes were found for Group 1, four for Group 2 and one for Group 3. These selected communes represented 40 of the 91 communes in Group 1 (44%), 117 of the 156 communes in Group 2 (75%) and 73 of the 95 communes in Group 3 (76.8%), i.e., 230 communes (67.3%). However, these communes did not comply with the second part of the criteria (provision of historical data on waste generation). Suitable secondary communes had to be selected using the same criteria in order to reduce the problem posed by the lack of available data.

As information was unavailable for the selected representative communes from Group 1, data was collected from the Municipality of *María Pinto* and from *Pichidegua*. Similarly, as representative communes from Group 2 could not provide data, the Municipalities of *Peumo* and *Purén* were contacted and their waste generation figures were obtained. Data from *Puerto Aysén* and *Puerto Natales* was also collected from governmental reports. In Group 3, data from *San Ramón* was collected as *Coronel* could not be contacted.

Finally, as these secondary communes are not the ones that best represent the other communes from their group, the level of coverage decreased to 36 communes for Group 1 (39.6%), 60 communes for Group 2 (38.5%) and 71 communes for Group 3 (74.7%). This reduced the overall total number of communes covered from 67.3% to 48.8%, i.e., from 230 to 167 communes. Even though the level of representativeness of the secondary communes is 18.5% smaller than that of the most representative communes, the level of coverage still remains satisfactory, as they represent almost half of the communes of Chile.

This method shows that, even though the best representative communes could not be used for representation due to lack of data, secondary communes have successfully represented a significant portion of the communes of Chile. In practical terms this means representing about 10.3 million people (68.2% of the population of Chile) and accounting for, with the aim of further improvement, a total of almost 330,000 tonnes a month of domestic solid waste (70.5% of DSW generated monthly in Chile). These figures should be seriously considered, bearing in mind the future potential for improving waste management practices and reducing its possible impact on social and environmental systems.

# CHAPTER 5

# STAGE 3: FORECASTING WASTE GENERATION

## 5.1 Literature Review

As discussed in Chapter 2, different authors have attempted to forecast waste generation using varied methods such as regression analysis models, time-series analysis, fuzzy models, mathematical techniques or computer simulations. The conclusions obtained from these methods and the analysed variables have led to varied and inconclusive results.

Regression analysis models have been widely used in forecasting waste generation but the results obtained from such models are unsatisfactory for several reasons. There are problems with the used variables and their data. Regression models also fail because they cannot learn from new data nor can they adapt to new situations. The conclusions drawn from regression models represent a snapshot of the problem without showing any trends or temporal relationships. Other authors have obtained better results using time-series models. However, there have been limitations with respect to the size of the required dataset or the assumed initial conditions. Methods such as sARIMA, non-linear techniques, grey fuzzy dynamic models and gray theoretical models have produced good results.

ANNs have not been previously applied in waste forecasting, however, they have been used successfully in the field of wastewater treatment. The success of ANNs is their capability of modelling non-linear problems with great accuracy. Their modelling is based on a learning process that occurs in each one of the neurons in the network as the data pass through from inputs to the output layer. Moreover, their capability of adaptation to unseen data and ability of some networks to capture temporal effects make them capable of forecasting desired behaviour reliably.

## 5.2 Modelling

Several MLPs and recurrent networks (Figure 2.1 (a), (c) and (d), respectively) were trained to forecast waste generation for the three groups determined in Chapter 4. The objective of this part of the study is to forecast amounts (and trends) in waste generation for the period up to 2010 from past and current data. In modelling terms, this involves forecasting next year's waste generation from previous year's explanatory variables. This time-series (dynamic) analysis is quite different from the analysis of waste generating factors done as a static case for the whole country in Stage 1. In a time-series, next outcome can be highly correlated with the current outcome (e.g. WG next year may be correlated to WG this year). This is possible because this year's outcome may capture substantially the effects of explanatory variables on the next outcome. However, time-series models can be further improved if the explanatory variables are also included to capture the aspects that are not accounted for by this year's data alone.

Unfortunately, the data for all the relevant explanatory variables found in Stage 1 was not available for all the past years due to the lack of consistent data collection in Chile. For example, Groups 1 and 2 only had POP and LIB and Group 3 had only POP and PUP. Data for EDU and IND could not be obtained for any of the communes (Appendix 15 shows data collected for the three groups). Lack of available data is a major problem for this study and Chilean authorities must address this point in order to make better use of the available advanced modelling methods.

Time-series were analysed using MLPs and recurrent networks. The difference between MLPs and recurrent networks is that recurrent networks use their outputs in one time step as inputs in the next time step thus creating their own internal representation of temporal effects whereas MLPs do not have feedback loops and learn solely from the past data fed externally as input. For some problems recurrent networks outperform MLPs but for others, MLPs with past data can work better. The reason is that any significant error in forecast in recurrent networks can propagate into the future through feedback loops. Training a recurrent network is similar to that of MLP in that inputs and target outputs are presented iteratively and weights adjusted until prediction error becomes acceptable.

Initially, MLP and recurrent networks were trained using only the explanatory variables for which data was available (i.e. POP, PUP or LIB). These used input data for the current year to forecast waste generation for the next year.

Many networks were tested and the best networks were recurrent networks with $R^2$ values reaching 0.75 for Group 1 and 0.80 for Group 3. Both Group 1 and Group 3 used POP as only input. The best network for Group 2 only reached $R^2$ of 0.25 with POP and LIB as inputs (Table 5.1).

Table 5.1: Forecasting Models of Waste Generation using POP, LIB and PUP as inputs (Initial Models)

| | Inputs | Net | $R^2$ | MSE |
|---|---|---|---|---|
| | POP, LIB | MLP | 0.6206 | 0.0087 |
| Group 1 ¢ | POP | Jordan | **0.7459** | 0.0058 |
| | POP | Elman | 0.0216 | 0.0223 |
| | Any | MLP | <0 | - |
| Group 2 £ | POP, LIB | Jordan | 0.1918 | 0.3025 |
| | POP, LIB | Elman | **0.2502** | 0.2807 |
| | POP, PUP | MLP | 0.7762 | 0.1521 |
| Group 3 ¥ | POP | Jordan | **0.7964** | 0.1384 |
| | PUP | Elman | 0.7829 | 0.1476 |

¢: Inputs from 1998 to 2003
£: Inputs from 1997 to 2002
¥: Inputs from 1992 to 2002

For Group 1, a Jordan recurrent neural network was the network with the best results for modelling waste generation for the group using POP as the only input. The dataset was divided into three sets: 40% for training the network, 30% for testing the model at various stages of training, and 30% for validation. The validation set is to test the model predictions on unseen data (generalisation). As shown in Table 5.1, the network modelled the relationship with $R^2 = 0.7459$ based on the validation dataset, and a correlation coefficient of 0.9846 based on the whole dataset. The architecture of the Jordan network had one neuron in the input layer, three in the hidden and one in the output layer. The input neuron used a linear function and both hidden and output neurons used logistic functions. The three layers were trained with a learning rate = 0.1, momentum = 0.1 and initial weight = 0.3. Training patterns were selected as a time-series. The number of training patterns to be processed since minimum average error on the test set was set at 20,000 as the stopping criterion and the test set was processed after every 200 training patterns to assess generalisation. The network was trained after 82,000 learning epochs (number of times the entire training set passes through the network) and 164,000 learning events (number of individual training patterns processed).

Figure 5.1 visually demonstrates the relationship between actual outputs and the network outputs for the whole dataset (correlation coefficient of 0.9846) and Figure 5.2 shows actual outputs superimposed on network outputs for the validation dataset ($R^2 = 0.7459$).

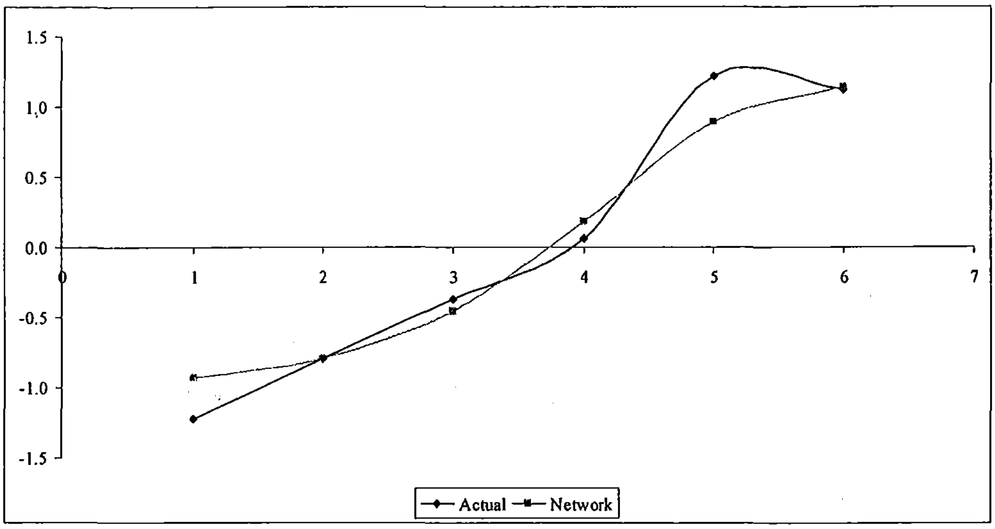



Figure 5.1: Actual Outputs superimposed on Network Outputs for the Whole Dataset of the Initial Model for Group 1

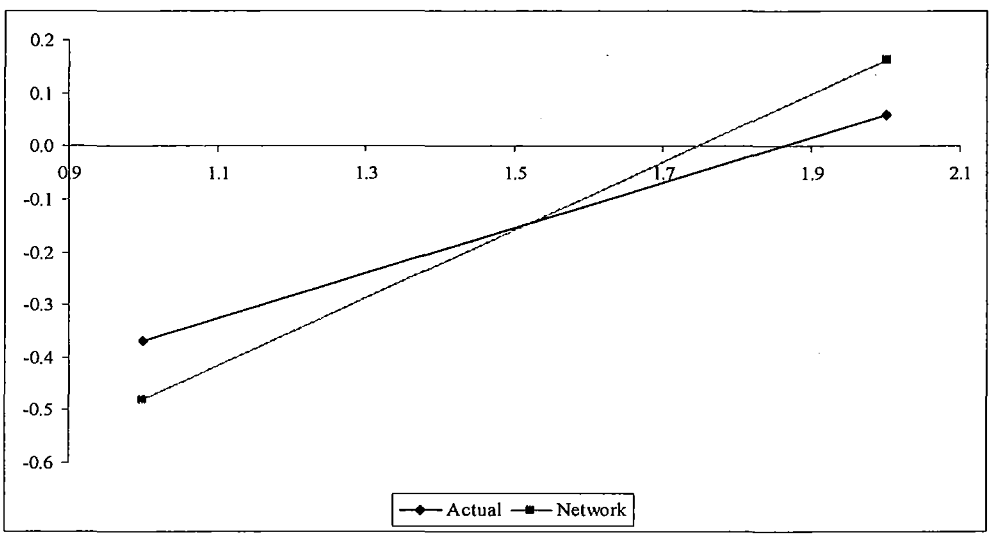



Figure 5.2: Actual Outputs superimposed on Network Outputs for the Validation Dataset of the Initial Model for Group 1

An Elman network was the selected network for Group 2 with POP and LIB as inputs. The dataset was divided into three sets: 40% for training, 30% for testing and 30% for validation. The network modelled the relationship with $R^2$ = 0.2502 based on the validation dataset, and a correlation coefficient of 0.7845 based on the whole dataset. The architecture of the network had two neurons in the input layer, three in the hidden and one in the output layer. The input neurons used a linear function and both hidden and output neurons used logistic functions. The three layers were trained with a learning rate = 0.1, momentum = 0.1 and initial weight = 0.3. The same stopping and test criteria as those used for the previous network for Group 1 were used here. The network was trained after 11,099 learning epochs and 22,200 learning events.

Figure 5.3 shows the relationship between actual outputs and the network outputs for the whole dataset (correlation coefficient of 0.7845) and Figure 5.4 shows actual outputs superimposed on network outputs for the validation dataset ($R^2 = 0.2502$).

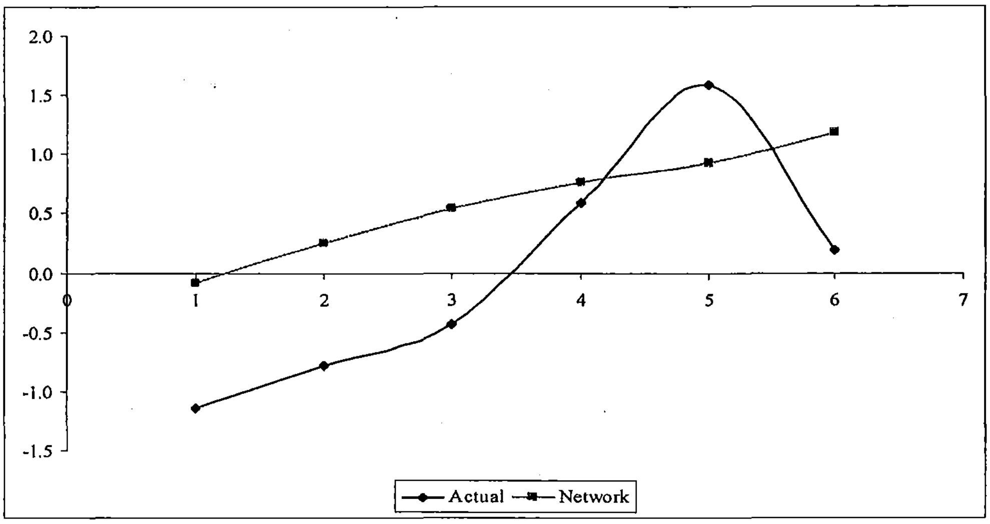



Figure 5.3: Actual Outputs superimposed on Network Outputs for the Whole Dataset of the Initial Model for Group 2

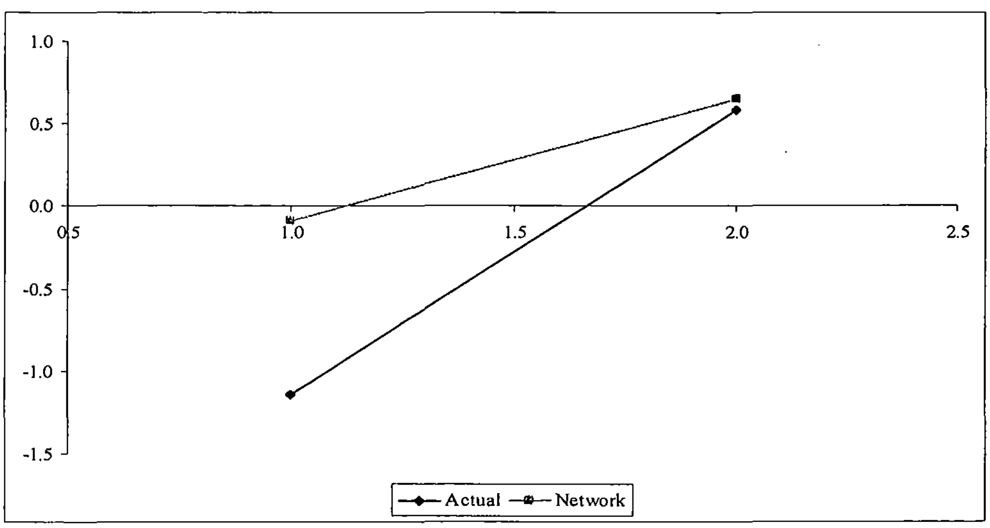



Figure 5.4: Actual Outputs superimposed on Network Outputs for the Validation Dataset of the Initial Model for Group 2

For Group 3, a Jordan network was the best network with just POP as input. The dataset was divided into three sets: 40% for training, 30% for testing and 30% for validation. The network modelled the relationship with $R^2 = 0.7964$ based on the validation dataset, and a correlation coefficient of 0.9101 based on the whole dataset. The architecture of the network had one neuron in the input layer, four in the hidden and one in the output layer. The input neuron used a linear function and both hidden and output neurons used logistic functions. The three layers were trained with a learning rate = 0.1, momentum = 0.1 and initial weight = 0.3. Test and stopping criteria were similar to those used in the previous two cases. The network was trained after 9,919 learning epochs and 49,600 learning events.

Figure 5.5 illustrates the relationship between actual outputs and the network outputs for the whole dataset (correlation coefficient of 0.9101) and Figure 5.6 shows actual outputs superimposed on network outputs for the validation dataset ($R^2 = 0.7964$).

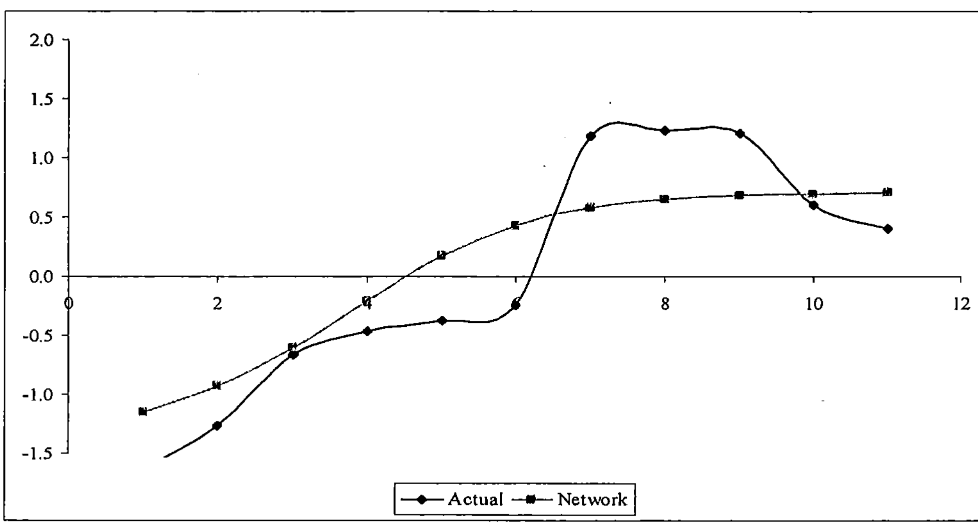



Figure 5.5: Actual Outputs superimposed on Network Outputs for the Whole Dataset of the Initial Model for Group 3

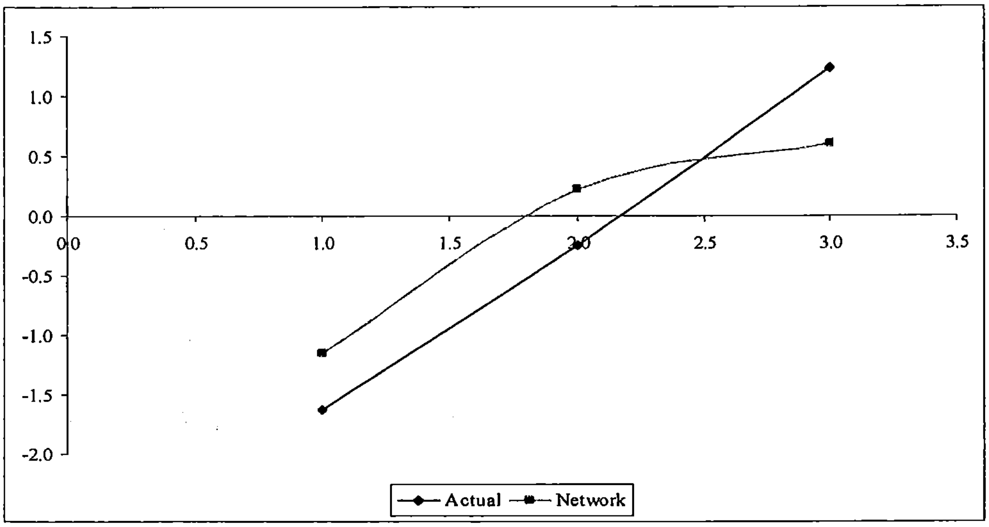



Figure 5.6: Actual Outputs superimposed on Network Outputs for the Validation Dataset of the Initial Model for Group 3

Appendix 16 shows plots of the training set average error versus the epochs elapsed and the testing set average error versus the intervals elapsed. It also shows actual outputs versus networks outputs, both for the whole dataset and validation set for the three networks.

The forecasted waste from the model for Group 1 (Table 5.1) is plotted in Figure 5.7 along with its yearly variation up to 2010 and the actual waste generation up to 2003. Figure 5.7 shows that the model forecasts are good (error between real and forecasted figures < 5%, Appendix 17) for the period from 1999 to 2002 for which most actual data was available for validation. The Jordan network forecasts that the waste for the representative commune of Group 1 will reach more than 100 tonnes/month by 2010. Moreover, it forecasts a steady increase in waste generation, reaching an annual rate of more than 3% by 2007-2008 and then dropping to less than 1% by 2010. The forecasts also show a 14.5% increase in waste for Group 1 for the period 2001-2010 (1.5% annual increase). Appendix 17 shows details of the results.

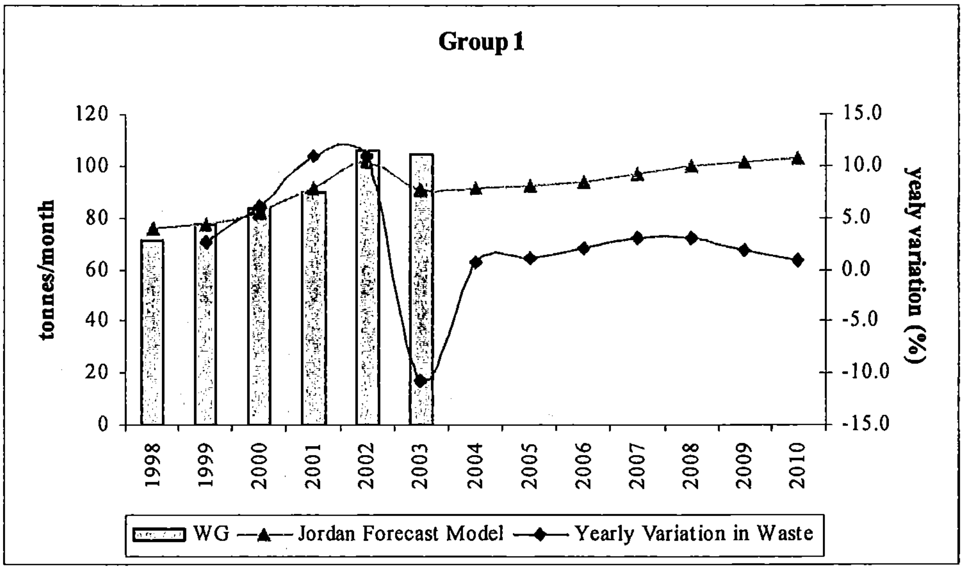



Figure 5.7: Waste Generation Forecasts up to 2010 of the Initial Model for Group 1

On the contrary, Figure 5.8 shows that the Elman model (Table 5.1) forecasts for Group 2 were not accurate for the period from 1997 to 2002 (error > 5%), for which network data was available for validation. The model forecasts that the level of waste generation will increase mildly up to around 235 tonnes/month by 2010, with an increase of 13.5% in the period 2002-2010 (1.6% annual increase). The annual variation in waste generation is forecasted to decrease from 1.7% in 2004 to just 0.4% by 2010. As the model is not capable of modelling most of the data for the validation period (1997-2002), these results are not reliable. Appendix 17 shows details of the results.

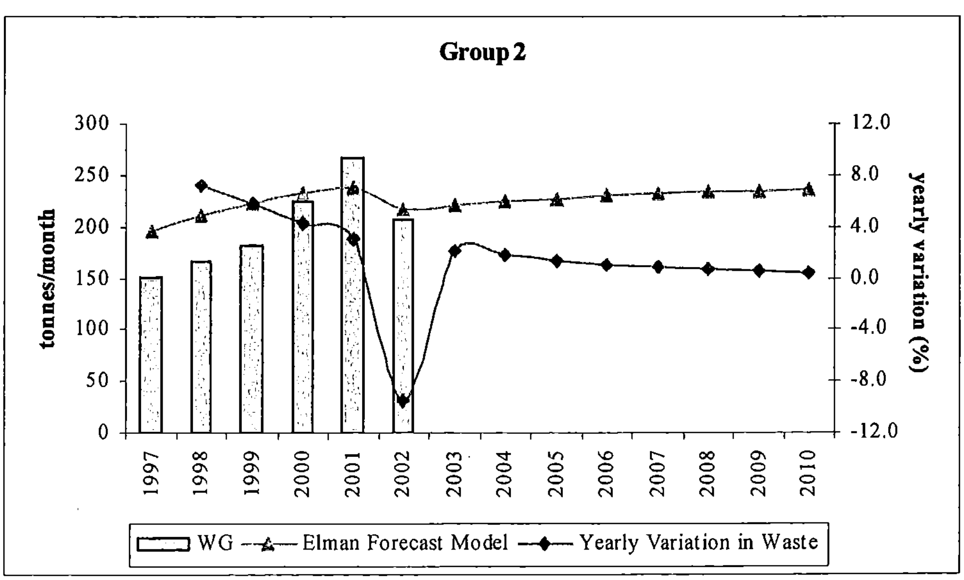



Figure 5.8: Waste Generation Forecasts up to 2010 of the Initial Model for Group 2

Finally, Figure 5.9 shows that the Jordan model forecasts for Group 3 are good for 1994-1995 and 2001-2002. For other years the error reaches levels greater than 5%. After 2002, forecasts show a steady increase in waste generation reaching almost 3,000 tonnes/month of waste by 2010, an increase of 5.2% in the period 2002-2010 (0.6% annual increase). The annual variation of WG is forecasted to continue its positive trend until 2005 (2.2%), but then falls to less than 1% in 2007, reaching almost 0% by 2010. Appendix 17 shows details of the results.

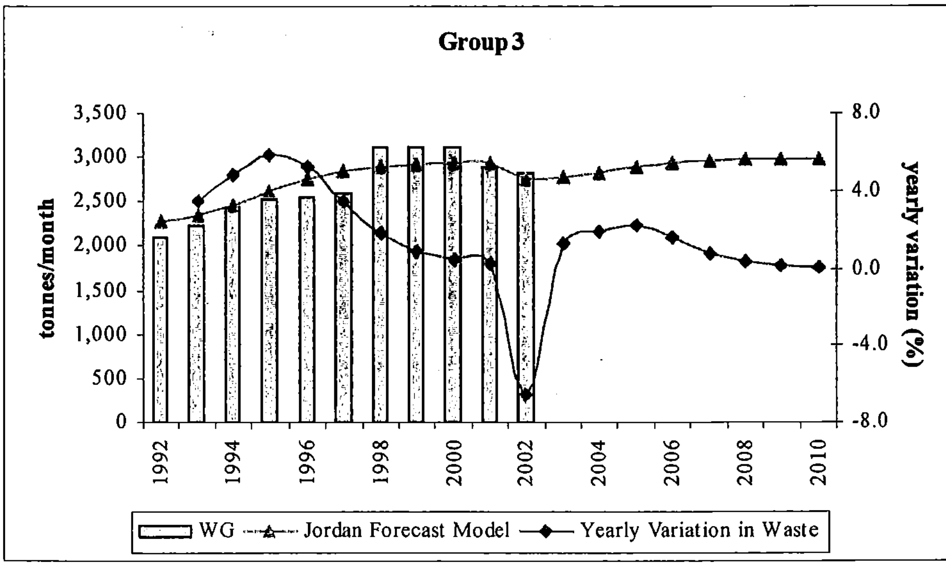



Figure 5.9: Waste Generation Forecasts up to 2010 of the Initial Model for Group 3

Next, in an attempt to improve forecasting accuracy, current per capita waste generation (PCWG) was used as an input, alone and in combination with the explanatory variables, to forecast waste generation next year (Appendix 18 shows data collected for the three groups). The best-selected networks are shown in Table 5.2, which shows that PCWG substantially captures the effect of explanatory variables in forecasting amounts of waste generation for the next year for the three groups.

Table 5.2: Forecasting Models of Waste Generation using PCWG as one of the inputs (Improved Models)

| | Inputs | Net | $R^2$ | MSE |
|---|---|---|---|---|
| | PCWG, LIB | MLP | **0.8138** | 0.0043 |
| Group 1 ¢ | PCWG | Jordan | 0.8015 | 0.0045 |
| | PCWG | Elman | 0.1468 | 0.9958 |
| | PCWG, LIB | MLP | **0.9071** | 0.0348 |
| Group 2 £ | PCWG, LIB | Jordan | 0.8979 | 0.0382 |
| | PCWG, LIB | Elman | 0.8688 | 0.0491 |
| | PCWG | MLP | 0.9460 | 0.0367 |
| Group 3 ¥ | PCWG | Jordan | **0.9813** | 0.0127 |
| | PCWG | Elman | 0.9456 | 0.0370 |

¢: Inputs from 1998 to 2003
£: Inputs from 1997 to 2002
¥: Inputs from 1992 to 2002

The best networks for Group 1 and 2 were MLP and for Group 3 Jordan. The addition of PCWG as an input increased the $R^2$ values for Group 1 from 0.75 to 0.81, Group 3 from 0.80 to 0.98. More importantly, $R^2$ for Group 2 rose substantially from 0.25 to 0.91, a difference that could be due to inaccuracies in the data for explanatory variables.

For Group 1, the MLP network gave the highest $R^2$ value with PCWG and LIB as inputs (Table 5.2). The dataset was divided into three sets: 40% for training, 30% for testing and 30% for validation. The network modelled the relationship with $R^2 = 0.8138$ based on the validation dataset, and a correlation coefficient of 0.9958 based on the whole dataset. The architecture of the MLP network had two neurons in the input layer, four in the hidden and one in the output layer. The input neurons used a linear function and both hidden and output neurons used logistic functions. The three layers were trained with a learning rate = 0.1, momentum = 0.1 and initial weight = 0.3. Input patterns were presented as a time-series. The number of training patterns passed since minimum average test error was set at 20,000 as for the earlier networks and the test set was processed after every 200 input patterns for assessing generalisation. The network was trained after 20,199 learning epochs and 40,400 learning events.

Figure 5.10 shows the relationship between actual outputs from the improved model and the network outputs for the whole dataset (correlation coefficient of 0.9958) and Figure 5.11 shows actual outputs from the improved model superimposed on network outputs for the validation dataset ($R^2 = 0.8138$). The figures visually demonstrate output accuracy and improvements over the previous model (Figures 5.1 and 5.2, respectively).

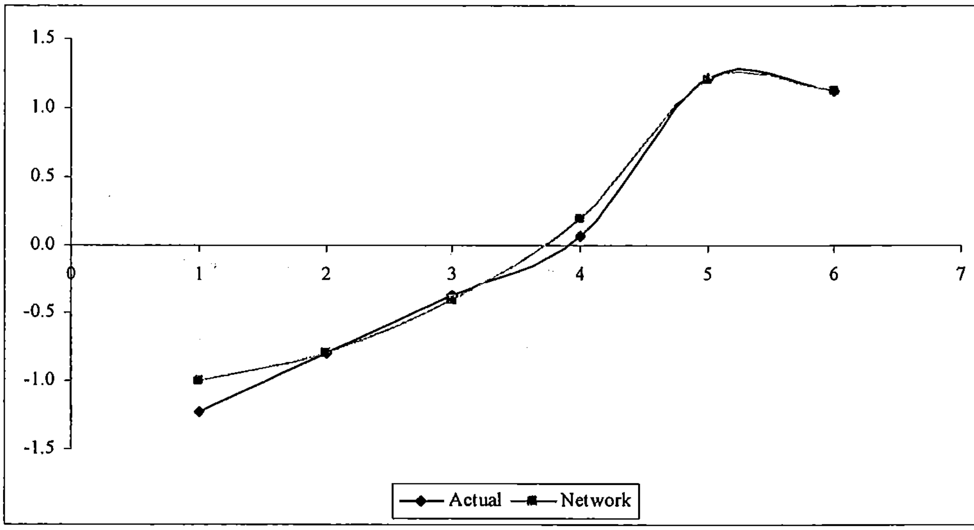



Figure 5.10: Actual Outputs superimposed on Network Outputs from the Whole Dataset of the Improved Model for Group 1

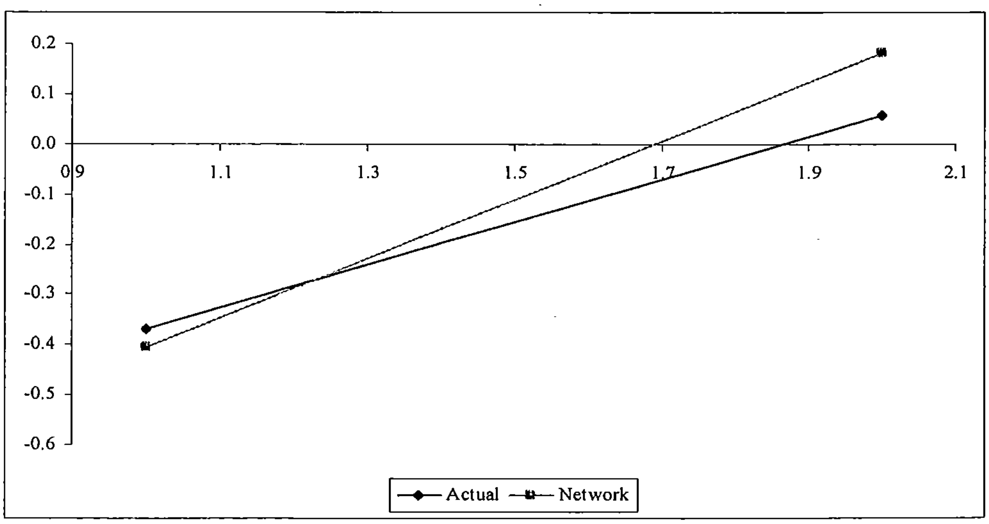



Figure 5.11: Actual Outputs superimposed on Network Outputs from the Validation Dataset of the Improved Model for Group 1

Another MLP network gave the highest $R^2$ value for Group 2, with PCWG and LIB as inputs (Table 5.2). The dataset was divided into three sets: 40% for training, 30% for testing and 30% for validation. The network modelled the relationship with an $R^2 = 0.9071$ based on the validation dataset, and a correlation coefficient of 0.9923 based on the whole dataset. The architecture of the MLP network had two neurons in the input layer, three in the hidden and one in the output layer. The input neurons used a linear function and both hidden and output neurons used logistic functions. The three layers were trained with a learning rate = 0.1, momentum = 0.1 and initial weight = 0.3. Training and test criteria were similar to the previous networks and the network was trained after 11,399 learning epochs and 22,800 learning events.

Figure 5.12 shows the relationship between actual outputs from the improved model and the network outputs for the whole dataset (correlation coefficient of 0.9923) and Figure 5.13 shows actual outputs from the improved model superimposed on network outputs for the validation dataset ($R^2 = 0.9071$). The figures visually demonstrate output accuracy and improvements over the previous model (Figures 5.3 and 5.4, respectively).

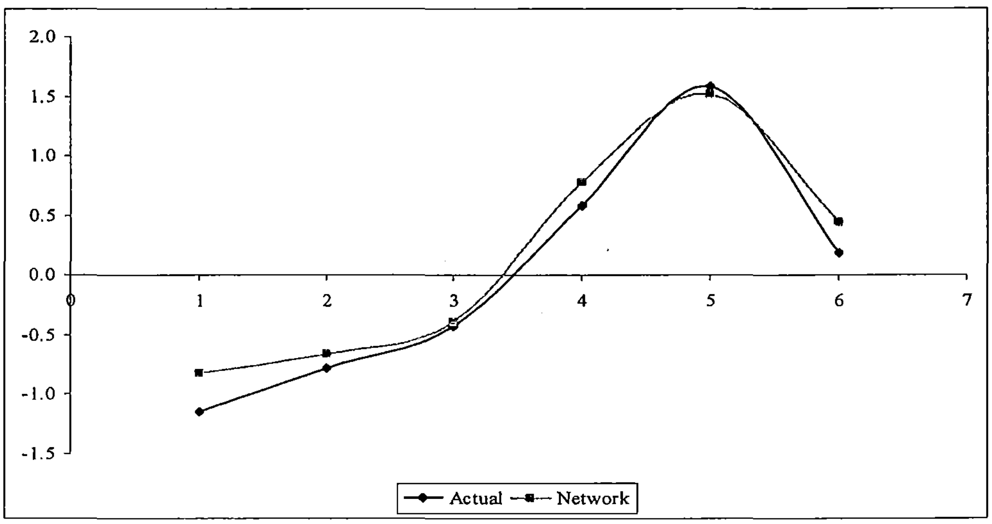



Figure 5.12: Actual Outputs superimposed on Network Outputs from the Whole Dataset of the Improved Model for Group 2

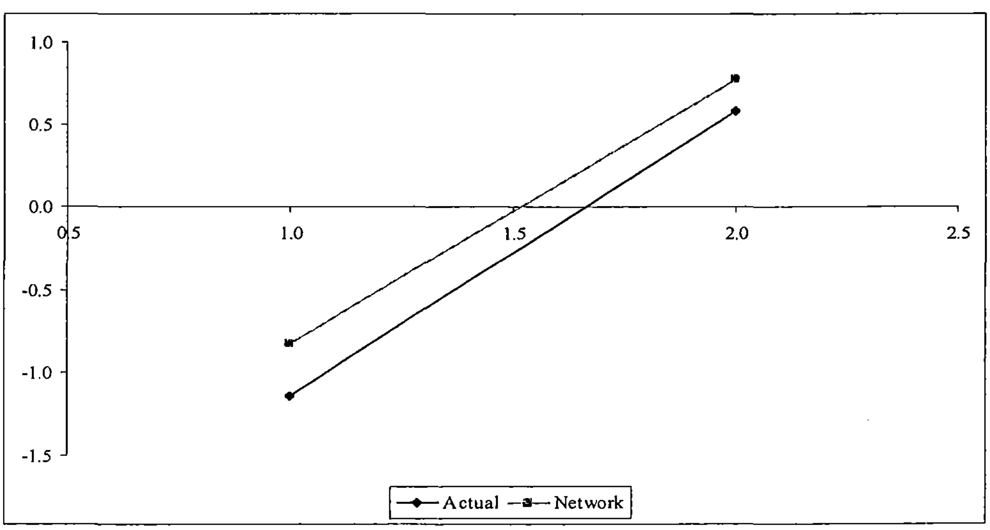



Figure 5.13: Actual Outputs superimposed on Network Outputs from the Validation Dataset of the Improved Model for Group 2

For Group 3, a Jordan recurrent network reached the highest $R^2$ value with PCWG as only input (Table 5.2). The dataset was divided into three sets: 40% for training, 30% for testing and 30% for validation. The network modelled the relationship with an $R^2$ = 0.9813 based on the validation dataset, and a correlation coefficient of 0.9966 based on the whole dataset. The architecture of the network had one neuron in the input layer, four in the hidden and one in the output layer. The input neuron used a linear function and both hidden and output neurons used logistic functions. The three layers were trained with a learning rate = 0.1, momentum = 0.1 and initial weight = 0.3. With similar test and training criteria as those used for other networks, this network was trained after 621,679 learning epochs and 3,108,400 learning events.

Figure 5.14 shows the relationship between actual outputs from the improved model and the network outputs for the whole dataset (correlation coefficient of 0.9966) and Figure 5.15 shows actual outputs from the improved model superimposed on network outputs for the validation dataset ($R^2$ = 0.9813). The figures visually demonstrate output accuracy and improvements over the previous model (Figures 5.5 and 5.6, respectively).

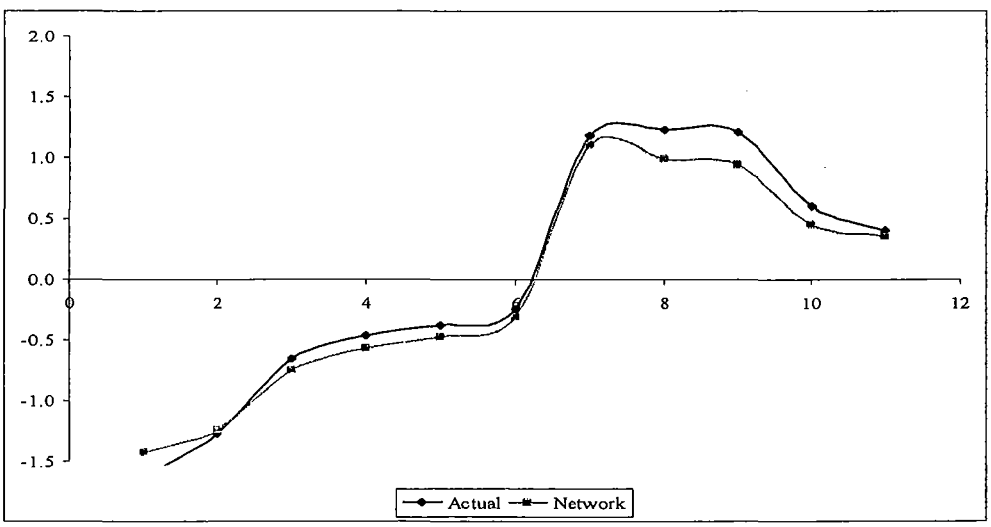



Figure 5.14: Actual Outputs superimposed on Network Outputs from the Whole Dataset of the Improved Model for Group 3

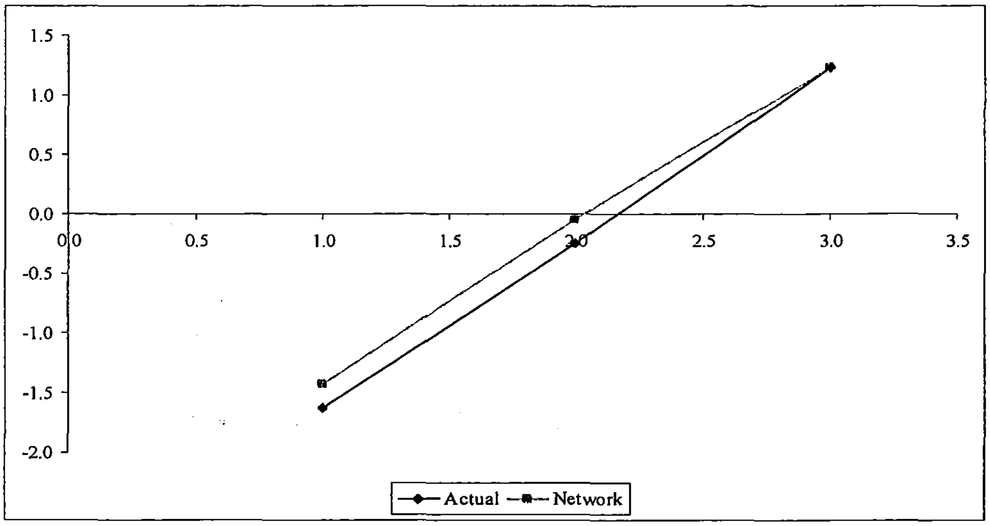



Figure 5.15: Actual Outputs superimposed on Network Outputs from the Validation Dataset of the Improved Model for Group 3

Appendix 19 shows plots of the training set average error versus the epochs elapsed and the testing set average error versus the intervals elapsed. It also shows actual outputs versus networks outputs, both for the whole dataset and validation set for the three improved networks.

A summary of the forecast trends from the improved models in waste generation is presented below for each representative commune.

The forecasted waste from the Group 1 best model (Table 5.2) is plotted in Figure 5.16 along with its yearly variation up to 2010 and the actual waste generation up to 2003. Figure 5.16 shows that the model forecasts are extremely accurate for the period from 1998-2003 (error < 5%, Appendix 20) for which actual data was available for validation. The best MLP network (Table 5.2) forecasts that the waste for the representative commune of Group 1 will reach more than 100 tonnes/month by 2010. It forecasts a steady increase in waste generation, reaching an annual rate of almost 4% by 2008 and then dropping to less than 1% by 2010. The variation in waste generation for the period 2001-2010 is forecasted to be 13.9% with an annual rate of 1.5%. Appendix 20 shows details of the results.

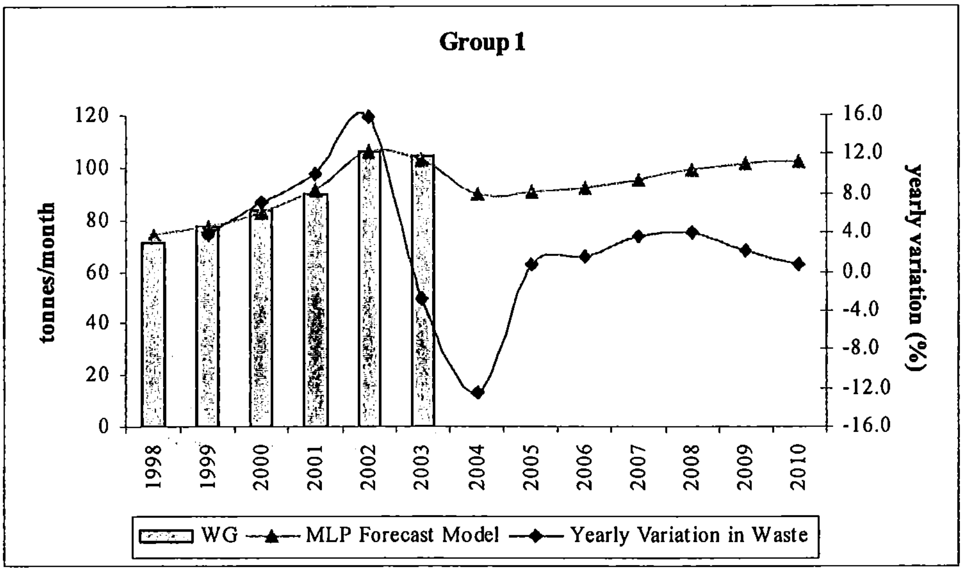



Figure 5.16: Waste Generation Forecasts up to 2010 of the Improved Model for Group 1

Figure 5.17 shows that the best MLP model (Table 5.2) forecasts for Group 2 were extremely accurate for the period from 1998 to 2002 (error < 5%) for which actual data was available for validation. The model forecasts that the level of waste generation will reach 240 tonnes/month by 2010, with annual increases of 1.9% in the period 2002-2010 (16% total increase in the same period). There will be a gradual increase in waste generation from 2003 reaching a peak of 3.5% rate of change in 2006 and then dropping to an annual rate of 0.6% by 2010. As expected, forecasts show that the annual rate of waste generation continues to be positive, a phenomenon that correlates with actual levels of WG and with the current lack of measures to minimise it. Appendix 20 shows details of the results.

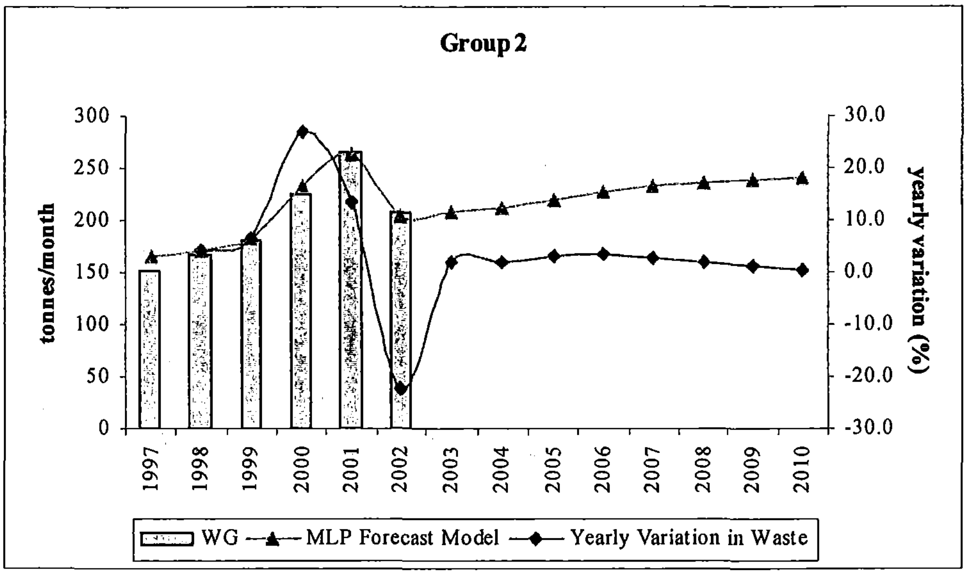



Figure 5.17: Waste Generation Forecasts up to 2010 of the Improved Model for Group 2

Figure 5.18 shows that the best model forecasts for Group 3 for the validation period (1992-2002) are extremely accurate (error < 5%). After 2002, there are fluctuations in the WG forecast and the model forecasts almost 2,900 tonnes/month of waste by 2010. The annual rate of change of WG peaks at 6% by 2006, reaches 0% by 2007-2008 and then keeps decreasing to almost –3% yearly rate in 2010. The rate of variation for the period 2002-2010 is 0.8% with annual increases of 0.1%. These results seem unlikely to occur considering the analysed variables and the continued increase in WG through the years. This phenomenon may happen in the commune selected as representative (San Ramón), which has had a decrease of 0.6% in its population (1992-2002) but not in Group 3 as a whole, which had a 1.3% increase in the same period. This appears to be a limitation of choosing this commune. Appendix 20 shows details of the results.

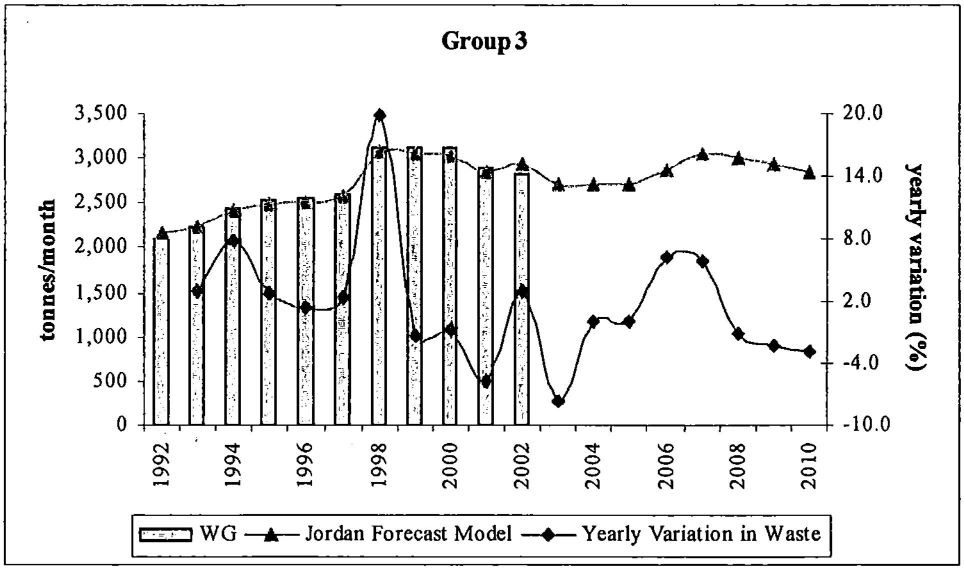



Figure 5.18: Waste Generation Forecasts up to 2010 of the Improved Model for Group 3

Both models, one with and the other without PCWG, showed similar trends and forecasts. However, all the models that incorporated PCWG as input showed a higher forecasting accuracy for the period for which actual data was available for validation (i.e., 1998-2003 for Group 1, 1997-2002 for Group 2 and 1992-2002 for Group 3). The models that incorporated PCWG were considered more accurate than those that did not.

### *5.2.1 Validation of Models*

A leave-one-out cross-validation analysis was developed for the three networks. Three validation tests were done where pairs of data were removed alternatively from the input datasets and the networks were rerun to estimate their generalisation ability, i.e., their performance on unseen data.

Table 5.3: Real Outputs against Validation Outputs for Group 1

| Scaled Output Values | REAL | VAL1 | VAL2 | VAL3 |
|---|---|---|---|---|
| 1998 | -1.22 | | -1.01 | -1.00 |
| 1999 | -0.80 | -0.61 | -0.78 | |
| 2000 | -0.37 | -0.39 | | -0.41 |
| 2001 | 0.06 | 0.06 | 0.33 | |
| 2002 | 1.21 | 1.20 | | 1.20 |
| 2003 | 1.12 | | 1.11 | 1.12 |
| **$R^2$** | | **0.985** | **0.962** | **0.988** |

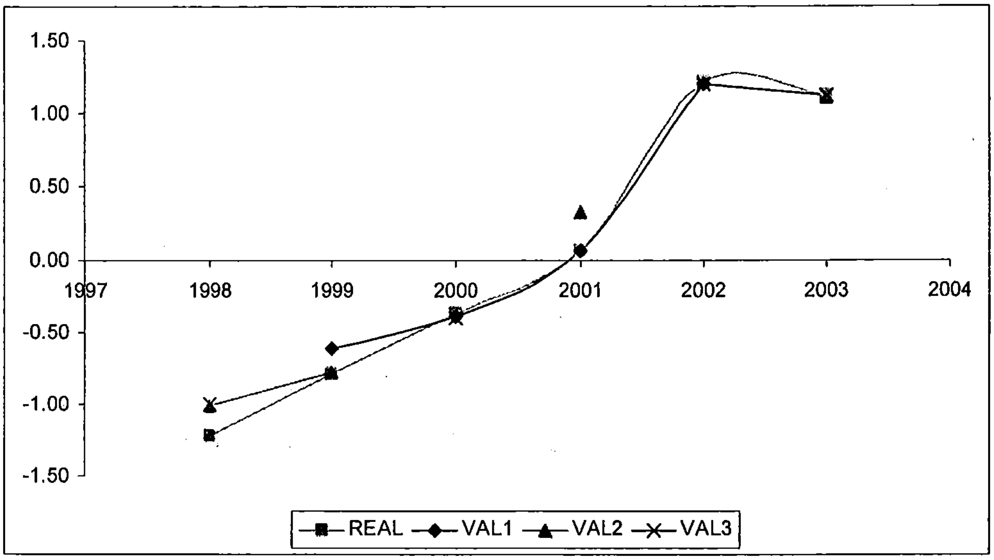



Figure 5.19: Real Outputs versus Outputs from Validation Tests (Group 1)

Table 5.4: Real Outputs against Validation Outputs for Group 2

| Scaled Output Values | REAL | VAL1 | VAL2 | VAL3 |
|---|---|---|---|---|
| 1997 | -1.15 | | -0.94 | -0.83 |
| 1998 | -0.78 | -0.51 | -0.75 | |
| 1999 | -0.43 | -0.33 | | -0.40 |
| 2000 | 0.58 | 0.72 | 0.55 | |
| 2001 | 1.58 | 1.53 | | 1.52 |
| 2002 | 0.19 | | 0.41 | 0.44 |
| **$R^2$** | | **0.968** | **0.952** | **0.958** |

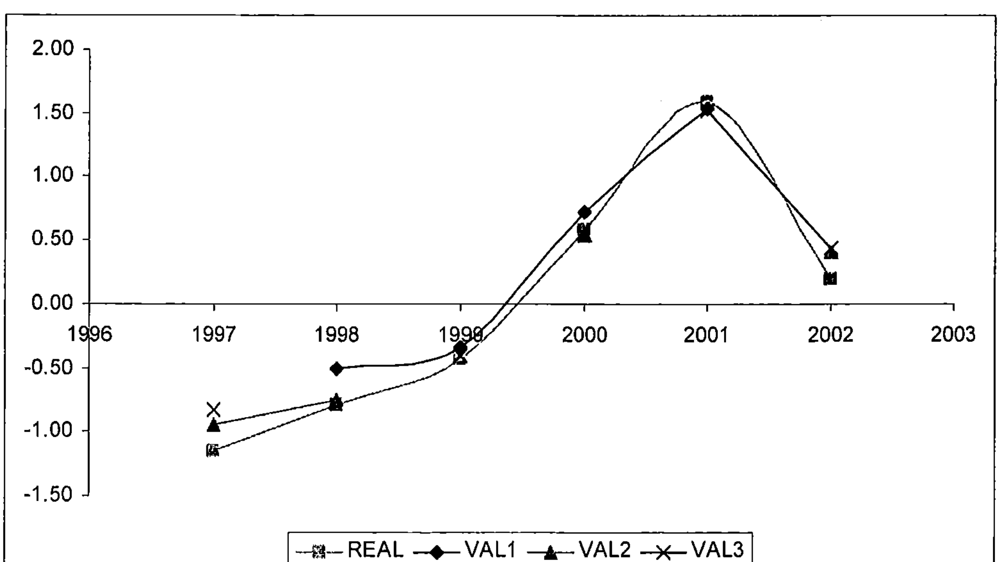



Figure 5.20: Real Outputs versus Outputs from Validation Tests (Group 2)

Table 5.5: Real Outputs against Validation Outputs for Group 3

| Scaled Output Values | REAL | VAL1 | VAL2 | VAL3 |
|---|---|---|---|---|
| 1992 | -1.63 | -1.43 | -1.43 | -1.43 |
| 1993 | -1.27 | -1.25 | | -1.24 |
| 1994 | -0.66 | -0.76 | -0.71 | -0.75 |
| 1995 | -0.46 | | -0.55 | -0.57 |
| 1996 | -0.38 | -0.43 | -0.47 | -0.47 |
| 1997 | -0.24 | -0.29 | -0.31 | -0.31 |
| 1998 | 1.18 | 1.10 | 1.11 | |
| 1999 | 1.23 | | 0.99 | 1.16 |
| 2000 | 1.21 | 1.01 | 0.94 | 1.01 |
| 2001 | 0.60 | 0.47 | | 0.48 |
| 2002 | 0.41 | 0.35 | 0.32 | |
| **$R^2$** | | **0.985** | **0.974** | **0.984** |

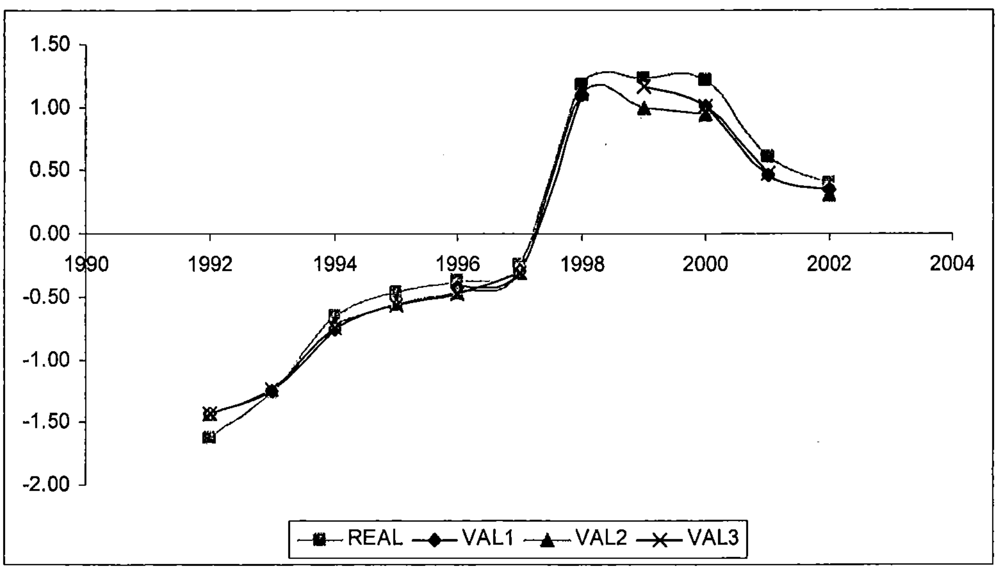



Figure 5.21: Real Outputs versus Outputs from Validation Tests (Group 3)

Despite the limited data, Tables 5.3, 5.4 and 5.5 show that the three networks are successfully validated reaching $R^2$ values greater than 0.95 in any of their validation models. Moreover, from Figures 5.19, 5.20 and 5.21 it can be seen that validation models are capable of generalising real values with great accuracy. This process demonstrates the validation of the networks.

## 5.3 Forecasts of Waste Generation for Represented Communes

As shown in Section 4.2.2.3, the three representative communes cover 167 communes: 36 from Group 1, 60 from Group 2 and 71 communes from Group 3. This section details the estimates of waste generation for the represented 167 communes up to 2010.

### *5.3.1 Method of Forecast*

In order to forecast waste generation for every one of the communes represented in each group, an annual conversion factor ($CF_i$) is created based on the representative communes' waste generation forecasts ($WG_{RC}$) and their levels of waste generation from previous years (starting from 2002). The conversion factor is determined by the following equation:

$$CF_i = \frac{WG_{RC,i} - WG_{RC,i-1}}{WG_{RC,i-1}} \qquad \text{(Eq. 5.1)}$$

$i$: year, from 2003 to 2010;
$RC$: Representative Commune.

The estimated level of waste generation for a represented commune $j$ in a year $i$ ($WG_{j,i}$) is determined from its waste generation from the previous year (starting from 2002) and the $CF$ for the respective year $i$.

$$WG_{j,i} = WG_{j,i-1} * (1 + CF_i) \qquad \text{(Eq. 5.2)}$$

where $j$ denotes a represented commune,

from 1st to 36th represented commune from Group 1,
from 1st to 60th represented commune from Group 2,
from 1st to 71st represented commune from Group 3.

### *5.3.2 Forecasts of Waste Generation for the Represented Communes*

In aggregated terms, the three groups of represented communes will behave in different ways for the projected period. Figure 5.22 shows total waste generated by the represented communes from the three groups. From the figure it can be seen that total waste from Group 1 will remain at a similar level up to 2010, total waste from Group 2 will increase steadily and total waste from Group 3 will peak in 2007 and then drop.

Table 5.6 shows that the 36 represented communes from Group 1 will increase their total waste generation from 3,400 tones/month to a peak of over 3,800 tonnes/month by 2010. The average waste generation level per commune will range from around 94 tonnes/month in 2004-2005 to 106 tonnes/month in 2010. There will be a slight decrease of 0.9% in total waste generation in 2010 with respect to 2002 levels. The table also shows that the 60 communes from Group 2 will increase their total waste generation up to over 18,500 tonnes/month by 2010, with an average per commune level of around 308 tonnes/month by 2010. This group will increase its waste generation by 16% from 2002 to 2010. Total figures from Group 3 show that the 71 communes will tend to decrease their total waste generation to roughly 295,500 tonnes/month by 2005, then increase to over 330,000 tonnes/month by 2007 and then drop just over 310,000 tonnes/month by 2010. The average waste generation level per commune will vary from around 4,100 tonnes/month to more than 4,600 tonnes/month. Group 3 will increase its waste generation by 7.5% in 2007 and then by 0.8% in 2010 from the 2002 levels.

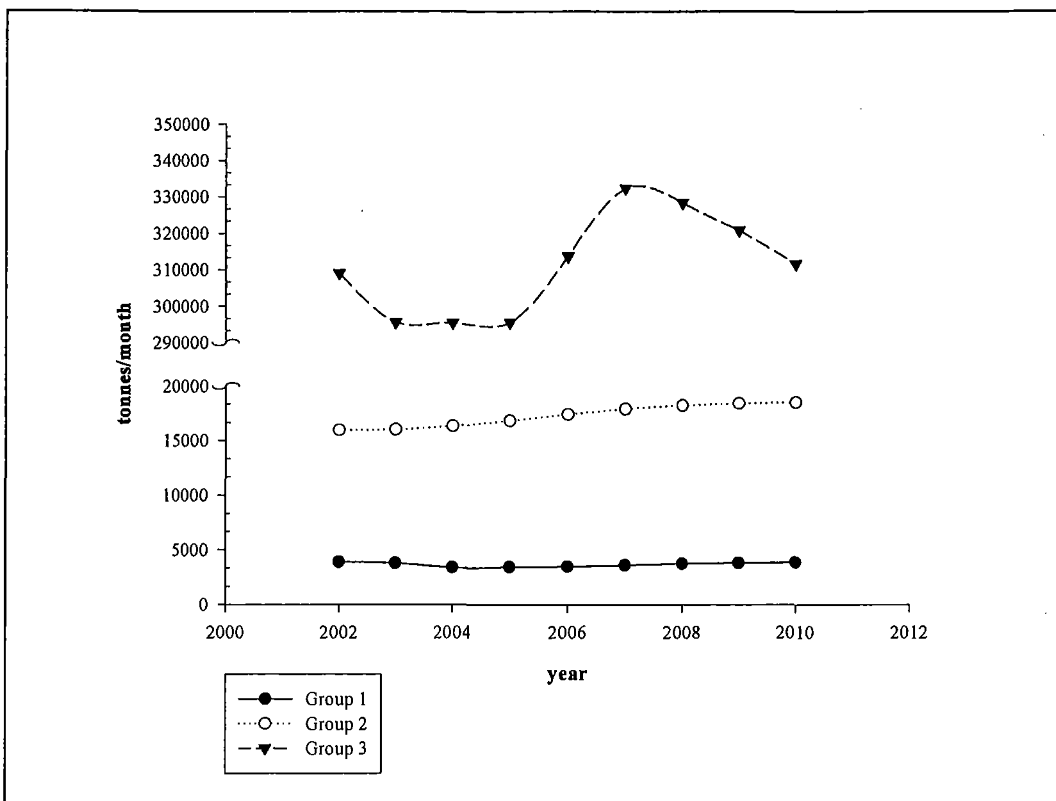



Figure 5.22: Total Forecasted Levels of Waste Generation for the Represented Communes up to 2010

Table 5.6: Total Forecasted Waste Generation for the 167 Represented Communes up to 2010

| tonnes/month | 2002* | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|---|---|---|
| Group 1 | 3,898 | 3,785 | 3,408 | 3,431 | 3,487 | 3,610 | 3,753 | 3,831 | 3,862 |
| Group 2 | 15,969 | 16,024 | 16,344 | 16,835 | 17,419 | 17,915 | 18,236 | 18,419 | 18,522 |
| Group 3 | 309,142 | 295,543 | 295,503 | 295,586 | 313,834 | 332,452 | 328,515 | 320,932 | 311,750 |
| TOTAL | 329,009 | 315,352 | 315,255 | 315,852 | 334,740 | 353,977 | 350,504 | 343,182 | 334,134 |

* Real values

Appendix 21 shows conversion factors for Groups 1, 2 and 3 along with the estimated levels of waste generation for every represented commune, and the mean and standard deviations up to 2010.

Table 5.7 shows that the 167 represented communes will reach a peak of 354,000 tonnes/month by 2007, dropping to 334,000 tonnes/month in 2010. If these communes continue representing 70.5% of the total waste generated in Chile (as they did in 2002 (Table 4.5)), the country will reach a peak of more than 500,000 tonnes/month by 2007, with a 7.6% increase in total waste from 2002 levels.

Table 5.7: Waste Generation from Represented Communes and Projected Levels for Chile up to 2010

| tonnes/month | 2002* | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|---|---|---|
| Represented Communes | 329,009 | 315,352 | 315,256 | 315,852 | 334,740 | 353,978 | 350,504 | 343,181 | 334,134 |
| Total Chile | 466,769 | 447,392 | 447,256 | 448,102 | 474,899 | 502,191 | 497,263 | 486,874 | 474,039 |
| Variation w/r to 2002 | - | -4.2% | -4.2% | -4.0% | 1.7% | 7.6% | 6.5% | 4.3% | 1.6% |

* Real values

### 5.4 Discussion and Conclusions

Past research on waste generation forecasting has been mainly done using multiple regression analyses and time-series models, both with certain limitations. Multiple regression models have analysed different sets of variables, reaching inconclusive results with respect to their contribution to waste generation. These multiple regression models have shown snapshots of waste generation instead of trends. Time-series models provide better results but are subject to large datasets and specific initial assumptions. ANNs have not been applied to waste generation forecasting, but they have performed successfully in solving problems in wastewater treatment. ANNs can provide a good alternative to forecast waste generation due to the capability of adaptation to unseen data, the capacity of modelling non-linear systems and their ability to model temporal effects. In this case study, the lack of data available in Chile has also made ANNs a good base for forecasting.

The objective of this part of the study was to forecast the quantity and trends of waste generation for the period up to 2010 using past and current data. However, data availability was a major limitation of this research. Even when a second set of representative communes was selected, the contributing data was not always available. Modelling for Groups 1 and 2 included POP and/or LIB, while the Group 3 models only used POP and/or PUP. Data for EDU and IND could not be obtained from any commune so these variables were not included. Despite the limited data, the models reached good $R^2$ values and learnt to model the desired output with good accuracy.

When predicting Waste Generation with POP, LIB and/or PUP as inputs, recurrent networks were found to be the best networks for the three groups. A Jordan network reached $R^2 = 0.746$ with POP as the input for Group 1, an Elman network used POP and LIB as inputs for Group 2 ($R^2 = 0.250$), and a Jordan network reached $R^2 = 0.796$ for Group 3 with POP as the input. When Per Capita Waste Generation (PCWG) was included as one of the inputs to forecast Waste Generation, the levels of accuracy improved significantly. MLPs used PCWG and LIB as inputs for Groups 1 and 2 and reached $R^2$ values of 0.814 and 0.907, respectively. Group 3 used just PCWG in a Jordan network and reached $R^2 = 0.981$. The improved models were successfully validated via a leave-one-out cross-validation analysis where three pairs of data were removed alternatively from the original dataset and the models were rerun to estimate their capability of generalisation. Results show that the validation models reached $R^2$ values greater than 0.95 for any of the three tests for the three groups.

The models with and without PCWG produced similar forecasts for the year 2010; however, the models that incorporated PCWG had an extremely high accuracy for the period for which real data was available for validation (i.e., 1998-2003 for Group 1, 1997-2002 for Group 2 and 1992-2002 for Group 3). Therefore, models that used PCWG were considered more reliable.

In the case of Group 1, the best model forecasts that the representative commune of the Group will reach waste generation levels of 100 tonnes/month by 2010. A steady increase in waste generation rates is also forecasted, reaching an annual rate of 4% by 2008 and then dropping to less than 1% by 2010. In Group 2, the best model forecasts an increase in WG to around 240 tonnes/month by 2010. The rate of WG will increase reaching a peak of 3.5% in 2006 and then dropping to 0.6% by 2010. In the case of Group 3, the best model forecasts waste generation to reach 2,900 tonnes/month by 2010. The yearly rate of change peaks over 6% by 2006 and then drops to –3% by 2010. This scenario seems unlikely considering the analysed variables and the continuing increase in WG. This phenomenon may occur in the selected commune (San Ramón), which has experienced a 0.6% decrease in population (1992-2002) but not in Group 3 as a whole (1.3% increase 1992-2002). This may be a limitation of selecting this commune.

In aggregated terms, total waste generation from the communes represented in Group 1 will range from 3,400 tonnes/month to over 3,800 tonnes/month by 2010, Group 2 communes will increase their total waste generation to over 18,500 tonnes/month by 2010, and communes from Group 3 will decrease their total generation to around 295,000 tonnes/month by 2005, and then waste generation will increase to over 330,000 tonnes/month by 2007, finally dropping to around 310,000 tonnes/month by 2010. The 167 represented communes will reach a peak of more than 350,000 tonnes/month by 2007, then drop to 334,000 tonnes/month by 2010. If the represented communes continue representing 70.5% of total waste generated (as was found from the analysis of 2002 data in Stage 1), Chile will reach a peak of more than 500,000 tonnes/month by 2007, with an increase of 7.6% in total waste generation from 2002. The total forecast for Chile by 2010 is around 475,000 tonnes/month.

This Chapter shows that despite limited data availability, ANNs have been capable of forecasting waste generation levels for the representative communes of every group with great accuracy. Based on the conclusions drawn from these models authorities should consider these figures when planning waste management systems. These figures could be used to take measures to minimise the potential impact of waste or to consider the current lack of applied measures to minimise, recycle or recover waste.

The method of research and the tools used in this section have been proven to perform successfully in forecasting waste generation. Forecasted figures are reliable based on the analysed variables and limited data availability (a major problem). The figures could be further improved if Chilean authorities improve consistency of data acquisition.

Chilean waste management authorities should consider the fact that waste generation has increased dramatically in the last decade and will continue to increase due to the current lack of measures to minimise it. The forecasted levels of waste generation can be considered as a guide to plan ahead and take measures to minimise future waste generation, implement recycling programmes thereby redirecting waste for alternative uses, or plan appropriate disposal facilities to reduce the environmental, social and economic impact caused by uncontrolled waste.

# CHAPTER 6

# 6. GENERAL DISCUSSION

## 6.1 Research Development

The problem of waste generation should concern authorities at all levels. Uncontrolled waste damages the environment by polluting the rivers, oceans and aquifers, and spreads diseases throughout communities. One significant problem is that despite the increased growth of recycling and recovery programmes worldwide, the actual levels of waste generation continue to increase.

In the particular case of Chile, there is a huge lack of information on waste generation levels. There are no recycling or recovery programmes across the country and most of the existing waste disposal facilities are operating either illegally or in an environmentally unsafe manner. At this stage, it is essential to identify the sources of waste generation in Chile with the aim of directing minimisation policies to where waste is actually generated, which in the long-term will tend to reduce waste generation. Moreover, it is fundamental to know the current levels of waste generation in communes as well as estimated amounts of waste generation in order to plan and design appropriate waste management systems to control the waste of the country.

Literature revision (Chapter 2) shows that several authors have analysed a long list of variables trying to understand the factors influencing waste generation as well as people's attitudes towards environmental issues such as green consumerism, recycling participation or waste generation. A variety of goals have pushed researchers to identify waste generating factors. Among these goals are: understanding the demand for waste collection services, designing a waste management plan, forecasting waste generation or understanding recycling attitudes. As a result, many factors have been found to contribute significantly to waste generation. The literature indicates that the most significant are population and income.

Until now, variables affecting waste generation in Chile were unknown due to the absence of adequate waste generation information. Waste reduction policies cannot be implemented until the variables affecting waste generation are identified. Without understanding the critical variables, minimisation policies are irrelevant and as a result, unsuccessful.

Proper estimations of waste generation can be made only after the factors contributing to waste generation are identified. Several authors have stated that estimations of future waste generation are fundamental for planning waste management systems as stated below:

- Estimates of generation rates of solid waste are the basis for the design and planning of solid-waste-management systems (Niessen, 1977, p. 544).
- With prevailing levels of regulation on landfilling siting and operations and the public opposition to landfill siting plans, it has become increasingly important that authorities have access to accurate and detailed forecasts of the quantities of solid waste generation (McBean & Fortin, 1993, p. 373).
- The amount of waste generated is essential for adequate decision-making regarding the management of solid waste (Buenrostro et al., 2001, p. 86).

In order to achieve the main aim and the objectives of this research (Chapter 1), a detailed method has been designed for development (Figure 1.2). The research method has been divided into three stages, each aiming for a specific result that is a basic condition to go on to the next stage as well as an independent outcome. In Stage 1 (Chapter 3), the most important factors contributing to waste generation in Chile have been identified. Identifying these factors makes valuable input to waste management in Chile. The result from Stage 1 is crucial for developing Stage 2 (Chapter 4), which aims for clustering communes into categories of waste generating communes. This provides a second independent contribution which helps to identify categories of waste generating communes. Then, for every group of communes, a representative commune was selected (Chapter 4). The selected representative communes were used for on-site research to achieve the aim of Stage 3 (Chapter 5). The aim of Stage 3 was to forecast waste generation levels up to 2010 for representative communes and extrapolate these results to the represented communes of each group.

## 6.2 Data Problems

There were several problems with the data. Once the required data were determined, the first problem raised was the uncertainty of data availability. Then, there was the problem of collecting the data, the existence of records from institutions related not only to waste management but also to waste-related variables. Later, there was trouble with the format of the data, meaning that it was not necessarily available for the same periods of time or in the same shape or form.

Once the data was collected, the process of determining which variables were more relevant for modelling waste generation was complicated due to the large number of variables. For cleaning the data, statistical analyses (multicollinearity and heteroskedasticity analyses) were run for determining the most significant variables. Firstly, the variables were classified as main and secondary variables depending on their capacity to correlate with waste generation (threshold at 70%). After running many statistical models, Population was selected as the representative variable from the group of main variables. The primary reasons were that it was the main variable included in the best model after heteroskedasticity was reduced and it was the one which correlated the most to every other main variable, making it capable of representing their respective influence on waste generation. The secondary variables were selected based on the condition of minimum correlation to each other and their predictive power in the best statistical model in which Population was included.

Once the communes were clustered based on the five variables determined on stage 1, the problem was on the availability of data for the most representative communes of every group. Based on a coverage range criterion, representative communes were selected for every group. Communal authorities were contacted and on-site visits arranged with the objective of data collection and developing on-site research. However, only limited records of data were found. None of the representative communes had enough or any information on waste generation. Therefore other less representative communes where data collecting had taken place had to be considered, reducing the level of representativeness of the groups from 67.3% to 48.8%.

Finally, on the third stage of this research, lack of data availability raised problems for the second set of representative communes. Out of the five most significant variables, only three could be used for forecasting waste generation because there was not enough data from previous years on the selected communes. ANNs need datasets from a number of years in order to be capable of forecasting future behaviour of any variable. As for two of the five variables there was only limited data, only the other three had to be used.

Despite the problems with the data, results show that the selected variables were capable of modelling waste generation, clustering three clearly different types of waste generating communes and forecasting waste generation for the representative communes.

**6.3 Results and Objectives**

Despite the fact that this study is limited by data availability, Artificial Neural Networks have been capable of working with (i.e., modelling, clustering and forecasting) the limited data obtained for this research with high accuracy. As discussed in Chapter 3, the five factors found to be the most important contributors to waste generation for Chile were determined using a Multi Layer Perceptron (MLP) neural network which, despite the problems with the data, modelled the relationship between the independent variables and waste generation with an $R^2 = 0.819$ on the validation dataset. Figure 3.1 shows high accuracy between actual waste generation figures and the outputs from the MLP. In order to compare the results from the MLP, a Multiple Linear Regression (MLR) analysis was run, proving this to be less representative ($R^2 = 0.615$). According to the results, the MLR was not as capable as the MLP of modelling waste generation with the five independent variables due to non-linearity of the data. This non-linearity was not a problem with ANNs. The MLP also showed that all the variables contribute positively to waste generation via 3D plots of all the variables (Appendix 6) and that Population is the most important factor for the case of Chile (Figure 3.5).

In Stage 2, a Self-Organising Feature Map neural network successfully clustered three very distinct groups of waste generating communes (Figure 4.1), confirming the good quality of the independent variables in terms of their significance to waste generation.

In Stage 3, recurrent neural networks were capable of forecasting waste generation for Groups 1 and 3 with high level of accuracy using a maximum of two variables as inputs (due to lack of data), although for Group 2 the $R^2$ value reached was just 0.25 (Table 5.1). This was possibly due to inaccuracies in the data. These results were improved significantly when current Per Capita Waste Generation (PCWG) was also included in MLPs and recurrent networks as one of the inputs (Table 5.2). Results show that PCWG substantially captures the effect of the explanatory variables in forecasting amounts of waste generation for the next year for the three groups. Models with PCWG as input were selected as the best predictors of waste generation due to their improved $R^2$ values and because the models' forecasts for the validation periods were extremely accurate for the three groups. These models were successfully validated via a leave-one-out cross-validation analysis which showed $R^2$ values greater than 0.95 for any of the three validation models applied to the three groups, demonstrating the increased capability of generalisation of the models.

Even though ANNs often require a large dataset to reach good results, it has been demonstrated here that they are capable of modelling, clustering and forecasting waste generation with high accuracy, even when subjected to the limited and sometimes inaccurate figures used in this research.

Finally, based on the estimates made with ANNs for the three representative communes and as a way to achieve the aim of covering an important portion of Chile, estimates of waste generation were made for the 167 represented communes. First, a conversion factor for the next year was created based on the forecasts made for the representative communes for the next year and on their levels of waste generation from the previous year. Then, the conversion factor for the next year and the represented commune's waste generation from the previous year were used to estimate the level of waste generation for a represented commune in the next year. The forecasts made for each representative commune as well as waste generation levels for each particular represented commune were put together to generate waste generation figures up to 2010 (Appendix 21). From these results and based on the representation of the represented communes in terms of total waste generation in 2002, estimates were made for the whole country. These estimates showed that there may be an increase of 7.6% in waste generation by 2007 with respect to 2002 figures at the country level (Table 5.7).

In conclusion, the specific objectives (Chapter 1, section 1.4) of this research have all been accomplished:

1. The most important (five) factors contributing to waste generation for Chile have been successfully identified (Chapter 3);
2. The communes of the country have been clustered into (three) waste generating groups (Chapter 4);
3. Representative communes have been selected for analysis (Chapter 4) and forecasts of waste generation for these communes have been made (Chapter 5);
4. Estimates have been used to forecast waste generation for a significant portion of the country (48.8% of the communes) (Chapter 5).

As a result, the main aim of designing a communal analysis tool to study waste generating factors and to forecast waste generation levels have been successfully achieved.

**6.4 Types of Artificial Neural Networks**

Different types of Artificial Neural Nets were used in the development of this research. Firstly, a Multi Layer Perceptron was used to establish the relationship between explanatory and the explained variables. Then, a Self Organising Feature Map to cluster the communes into distinct groups. Finally, MLPs and recurrent networks were used to forecast waste generation.

To establish the relationship between the explanatory and the explained variable it was necessary to associate these variables in a model. One of the properties of MLP networks was to learn to recognise and classify patterns autonomously via supervised learning and a back-propagation training algorithm, a gradient-descent method used to minimise the error of prediction. This learning process trains the network to produce very good outputs for unseen inputs. MLPs have been used in many applications such as function approximations, speech identification, forecasting and control. This network was capable of approximating the value of the variable waste generation from the five explanatory variables found to be the most significant with high accuracy, while showing their relative contribution to waste generation..

After the explained variables were determined, groups of waste generating communes were needed to be identified to focus the development of the research on representative communes. To achieve this immediate goal, it was necessary to use an algorithm which was capable of clustering data by following similar patterns and placing the similar patterns into groups. Kohonen's Self Organising Feature Maps were the networks capable of developing such a task. SOFMs are a competitive unsupervised learning network which defines a spatial network for each output unit with the capability of topology preservation. SOFMs have been used for clustering, categorisation and data analysis. The network used for clustering in this research was capable of clustering three very distinct groups of waste generation communes.

Finally, for forecasting waste generation levels, MLPs and recurrent networks were tested based on their properties on data prediction. MLPs have been used for forecasting due to their suitability for nonlinear predictions. Recurrent nets have been designed in such a manner that their outputs reflect the current as well as previous values of inputs and outputs, i.e., the current prediction is always based on the previous one. This differs from MLPs which need a number of static inputs for forecasting the following time period.

The results obtained in this research show that Artificial Neural Networks are a very useful and powerful tool which has helped in the recognition of patterns of waste generation, in clustering groups of waste generating communes and in forecasting waste generation levels for a very important number of communes in Chile. This research has proven that working with ANNs represent an advantage in terms of using the same technique in different aspects with such a great accuracy.

### 6.5 Contribution

The approach developed in this research aims for designing a thorough tool for analysis of waste generation. Identifying waste generating factors and how these factors contribute and relate to waste generation is essential for understanding why waste is being generated, where policies should be directed and how waste generation might evolve based on the development of these factors. Waste authorities should focus on waste generating factors to be able to proactively address waste generation at its source, rather than wait to react to the generated waste. The approach of clustering communes is very useful for identifying types of waste generating communes, designing collective policies as well as developing waste management programmes. Representative communes can be considered "communes of control", where projects and programmes can be tested and then applied to the represented communes due to their waste generating similarities. Finally, as earlier cited, it is essential to have estimates of waste generation in order to plan waste management systems capable of managing waste in an appropriate manner. Otherwise, recycling programmes, collection and transporting designs as well as disposal facilities are at risk of not being able to handle real (unexpected) amounts of waste with environmental, social and economic repercussions. Adequate forecasts of waste generation give authorities valuable information to make decisions accordingly.

The study presented here forms the first approach to waste management for the case of Chile. Waste generating factors had never been identified or studied before in Chile. In this study, the 342 communes of the country have been successfully clustered based on the properties of their waste generating factors. Forecasts of waste generation had not been made for Chile or for any portion of the country. While this research has been developed in Chile as a case study, this model can be applied to different sets of cities, states or countries, adjusting the waste generating factors accordingly to the desired region.

As discussed in the literature revision (Chapter 2), none of the previous studies identified waste generating factors using a methodical approach as it has been done here. Basically, they have all arbitrarily selected variables that seem to affect waste generation and then determined their significance to waste generation. That may be one of the reasons why relevant and not so relevant variables were found. This research did not start from selected variables but rather from a large list of possible variables, which after processing led to the significantly important factors. Moreover, previous forecasts of waste generation had not been made based on the most important variables contributing to waste generation, but only on variables which were thought to be capable of forecasting waste generation. The method used in this research is a new approach and a contribution to this field. For forecasts to be accurate and reliable, the factors used as inputs must be the best and most important factors contributing to waste generation.

### 6.6 Limitations and Further Research

The main limitation of this research was the data availability, a serious problem from the beginning of the study. To determine waste generating factors, data for 34 variables for the 342 communes of Chile was collected from public institutions. This dataset contained information from different years and in some cases was incomplete. These inaccurate or incomplete figures may have affected the results obtained from the multicollinearity and heteroskedasticity analyses. One variable that could not be included in the analysed list is the consumption level of the population. There were no records on consumption levels on communal basis in Chile. This variable could only be found as a retail statistic which is in a format not useful for this research. This is a very interesting variable which, a priori, seems to be highly correlated with waste generation, and may be worth considering in further research. Another variable which literature showed to be important to waste generation was the existence of tipping fees. This variable cannot yet be considered in Chile, as Municipalities have only recently started charging for the rubbish collection service.

In Stage 2, only data for the most important variables contributing to waste generation were used. Figures for the variables Population, Percentage of Urban Population and Number of Libraries were complete, but data for Indigent Population and Years of Education showed gaps for some communes and regional averages had to be used to complete the dataset. These average figures might have overestimated real values. After representative communes were determined, it was found that these communes all lacked data. Secondary communes had to be used instead as representatives, reducing the representativeness capacity of the approach. It is important to mention that ANNs would have been capable of clustering the communes into a larger number of groups, but due to the time limitations and economic restraints of this research, more communes could have not been assessed during the on-site research period. This fact should be considered for further research because more specific groups may represent a larger number of communes through the representative communes approach, improving the representativeness of the model.

When forecasting waste generation, figures for Indigent Population and Years of Education could not be used as inputs on the networks because these were not available for the representative communes. Thus forecasts were made only with the other three variables. Data was available from a limited number of years (six for Groups 1 and 2 and eleven for Group 3) with gaps in between years. These gaps had to be filled with proportional estimates. Waste Generation, as the output variable, also showed problems for some communes. The obtained data was not recorded per commune but by disposal facility. These disposal facility figures represented waste generation from a group of communes and proportional estimates had to be made to calculate waste generation per commune. These estimates might have influenced further results. Data from the 1990's might be underestimated because record keeping of waste generation levels was not a common practice and, as most of the disposal facilities were (and still are) illegal and uncontrolled, the real amount of waste being disposed at these facilities is unknown. This explains the discrepancy between the large increase in waste generation shown in Table 1.1 (66.7%) and the forecasted figures. As data from 1996 seems to be underestimated the difference between such figures and data from 2002 should be much smaller (forecasted figures are very much influenced by Population and therefore, the models follow the trend in Population, which represents only a small change). Moreover, in the last year used for validation (Figures 5.16, 5.17 and 5.18), there seems to be a miscalculation in the original data because figures are lower in comparison to previous years. One reason may be that these data had not been updated at the time of collection (2003).

Finally, extrapolated figures to the represented communes also suffer from errors due to problems with the original data. Waste generation data for some represented communes from 2001 and 2002 seem to be inconsistent. According to the figures some communes increased its waste generation enormously in 2002 with respect to 2001, while others reduced it dramatically. Both issues have no clearer explanation than possible data errors; therefore forecasts for these communes should be checked and considered only on the basis of the obtained data.

In order to improve the results obtained in this study, further research is encouraged based on the data limitations of this research. A more complete and accurate dataset would improve the accuracy of the results found in this study. With a more complete dataset, more precise contribution figures might be found providing a better understanding of how variables relate to waste generation. Communes would be clustered in a more exact manner and perhaps more distinctive groups could be found. If the representative communes have data on waste generation, the representativeness of the model would reach a higher level, representing a much larger number of communes. Finally, with more data, all the explanatory variables could be used as inputs in the forecasting models, improving the accuracy in the validation periods and making better forecasts.

Based on the good results obtained in this research, a more detailed study on waste composition and recovery markets is encouraged for the case of Chile. The same approach can be developed to assess components of current waste generation in Chile. Moreover, in order to recover the generated materials, the existence of current and the creation of potential recovery markets should be assessed. This would encourage the use of the generated amounts of waste-components as productive raw materials. This would minimise waste to disposal sites enlarging the disposal site's operating life. It would also reduce environmental damage and create employment in local economies.

Finally, even though ANNs have not widely been applied to waste management problems, it has been demonstrated here that they have the potential to work with waste data to produce results with high accuracy. As the results from this research show, despite the problems with the data, ANNs have solved the proposed tasks with a high degree of success. This demonstrates that neural networks have real potential if an adequate dataset is provided.

# ACRONYMS

ACF: AutoCorrelation Function

ANNs: Artificial Neural Networks

ANOVA: Analysis of Variance

ARIMA: AutoRegressive Integrated Moving Average

ARMA: AutoRegressive Moving Average

BID: *Banco Interamericano de Desarrollo* (Inter-American Development Bank)

BOD: Biochemical Oxygen Demand

C: Coverage Range

CF: Conversion Factor

CONAMA: *Comisión Nacional del Medio Ambiente* (National Commission for the Environment)

CURT: Cubic Root

DSW: Domestic Solid Waste

EDU: Years of Education

EIA: Environmental Impact Assessment

FP: Fifth Power

G1: Group 1

G2: Group 2

G3: Group 3

GF: Grey Fuzzy

GDP: Gross Domestic Product

HDI: Human Development Index

IND: Number of Indigents

INE: *Instituto Nacional de Estadísticas* (National Institute of Statistics)

LIB: Number of Libraries

LOG: Logarithm

LSM: Least Squares Method

MIDEPLAN: *Ministerio de Planificación* (Ministry of Planning)

MLP: Multi-Layer Perceptron

MLR: Multi-Linear Regression

MSE: Mean Square Error

MSG-EE: Multi-Sectoral Equilibrium

MR: Metropolitan Region

NP: Non-poor

PC: Per Capita

PCWG: Per Capita Waste Generation

POP: Population

PPP: Purchasing Power Parity

PUP: Percentage of Urban Population

RC: Representative Commune

sARIMA: Seasonal AutoRegressive Integrated Moving Average

SESMA: *Servicio de Salud Metropolitano del Ambiente* (Environmental Metropolitan Health Service)

SOFM: Self-Organising Feature Map

SQRT: Square Root

SS: Suspended Solids

ULS: Unconditional Least Square

UNDP: United Nations Development Programme

USEPA: United States Environmental Protection Agency

WG: Waste Generation

# REFERENCES


Ali Khan, M. Z., & Burney, F. A. (1989). Forecasting Solid Waste Composition - An Important Consideration in Resource Recovery and Recycling. *Resources, Conservation and Recycling, 3*, 1-17.

Arey, M. J., Baetz, B. W., Macdonald, P. D., & Byer, P. H. (1993). Use of Mixed Probability Distributions for the Analysis of Solid Waste Generation Data. *Waste Management Research, 11*, 387-402.

Bagby, J., Ernsdorff, S., Kipperberg, G., & Perrin, L. (2001). Seattle's Solid Waste Plan: On the Path to Sustainability (pp. 46).

Banco Central de Chile. (1999). *Población Estimada al 30 de Junio, según Regiones, Provincias y Comunas 1995-1999 (Estimated Population at June 30th, according to Regions, Provinces and Communes 1995-1999).* Santiago de Chile: Banco Central de Chile.

Banco Central de Chile. (2002a). *Inversión Extranjera Materializada (D.L. 600) según región 1990-2000 (Materialised Foreign Investment (Act. 600)) per region 1990-2000).* Santiago de Chile: Banco Central de Chile.

Banco Central de Chile. (2002b). *Producto Interno Bruto Regional por Clase de Actividad Económica (Regional Gross Domestic Product per Class of Economic Activity).* Santiago de Chile: Banco Central de Chile.

Banco Central de Chile. (2002c). *Statistical Synthesis of Chile 1997-2001.* Santiago de Chile: Department of Research Division Management - Banco Central de Chile.

Banco Central de Chile. (2003). *Participación Regional en el Producto Interno Bruto Regionalizado (Regional Participation in the Regionalised Gross Domestic Product).* Santiago de Chile: Banco Central de Chile.

Bridgwater, A. V. (1986). Refuse Compositions Projections and Recycling Technology. *Resources and Conservation, 12*, 159-174.

Bruvoll, A. (2001). Factors Influencing Solid Waste Generation and Management. *The Journal of Solid Waste Technology and Management, 27*(3&4).

Bruvoll, A., & Ibenholt, K. (1997). Future Waste Generation. Forecasts on the Basis of a Macroeconomic Model. *Resources, Conservation and Recycling, 19*, 137-149.

Buenrostro, O., Bocco, G., & Vence, J. (2001). Forecasting Generation of Urban Solid Waste in Developing Countries - A Case Study in Mexico. *Journal of Air & Waste Management Association, 51*, 86-93.

Cailas, M., Kerzee, R., Bing-Canar, J., Mensah, E., Croke, K., & Swager, R. (1996). An Indicator of Solid Waste Generation Potential for Illinois Using Principal Components Analysis and Geographic Information Systems. *Journal of Air & Waste Management Association, 46*, 414-421.

Calderón, Z., Espuña, A., & Puigjaner, L. (1998). Waste Analysis and Minimization in Batch and Semibatch Reactor Operation Through Dynamic Simulation and Neural Networks. *Computers & Chemical Engineering, 22*(1), S997-S980.

Chang, N.-B., & Lin, Y. T. (1997). An Analysis of Recycling Impacts on Solid Waste Generation by Time Series Intervention Modeling. *Resources, Conservation and Recycling, 19*, 165-186.

Chang, N.-B., Pan, Y. C., & Huang, S. (1993). Time Series Forecasting of Solid Waste Generation. *Journal of Resource Management and Technology, 21*(1), 1-10.

Chen, H. W., & Chang, N.-B. (2000). Prediction analysis of solid waste generation based on grey fuzzy dynamic modeling. *Resources, Conservation and Recycling, 29*, 1-18.

Chu, P., & Chiu, J. (2003). Factors Influencing Household Waste Recycling Behavior: Test for an Integrated Model. *Journal of Applied Social Psychology, 33*(3), 604-626.

Comisión Nacional del Medio Ambiente - CONAMA. (1997). *Gestión Integral de Residuos Sólidos Domiciliarios: Política (Domestic Solid Residues Integrated Management: Policy)*. Santiago de Chile: CONAMA.

Comisión Nacional del Medio Ambiente - CONAMA. (2002a). *Volúmenes y Clasificación de los Residuos en el año 2001 a Nivel Nacional - Metas Reciclaje Nacional 2005 (Volumes and Classification of Residues in 2001 at National Level - National Recycling Goal 2005)*. Santiago de Chile: CONAMA.

Comisión Nacional del Medio Ambiente - CONAMA. (2002b). *Agenda Ambiental País: Por un Desarrollo Limpio y Sustentable 2002-2006 (Environmental Agenda: For a Clean and Sustainable Development 2002-2006)*. Santiago de Chile: CONAMA.

Comisión Nacional del Medio Ambiente - CONAMA. (2002c). *Mayoría de vertederos existentes son ilegales (Most of the existing dumping sites are illegal)*. Santiago de Chile: CONAMA.

Comisión Nacional del Medio Ambiente - CONAMA. (2002d). *Catastro Nacional de Vertederos y Rellenos de Residuos Sólidos Domiciliarios 2001 (National Report on Domestic Solid Waste Landfills and Dumping Sites 2001).* Santiago de Chile: CONAMA.

Comisión Nacional del Medio Ambiente - CONAMA. (2003). *Catastro Nacional de Vertederos y Rellenos de Residuos Sólidos Domiciliarios 2002 (National Report on Domestic Solid Waste Landfills and Dumping Sites 2002).* Santiago de Chile: CONAMA.

Dinda, S. (2004). Environmental Kuznets Curve Hypothesis: A Survey. *Ecological Economics, 49*(4), 431-455.

Dong, C., Jin, B., & Li, D. (2003). Predicting the Heating Value of MSW with a Feed Forward Neural Network. *Waste Management, 23*, 103-106.

Ebreo, A., Hershey, J., & Vining, J. (1999). Reducing solid waste: Linking recycling to environmentally responsible consumerism. *Environment and Behavior, 31*(1), 107.

El-Din, A. G., & Smith, D. W. (2002). A Neural Network Model to Predict the Wastewater Inflow incorporating Rainfall Events. *Water Research, 36*, 1115-1126.

Folz, D., & Hazlett, J. (1991). Public Participation and Recycling Performance: Explaining Program Success. *Public Administration Review, 51*(6), 526.

Grossman, D., Hudson, J., & Marks, D. (1974). Waste Generation Models for Solid Waste Collection. *Journal of The Environmental Engineering Division, 100*(EE6), 1219-1230.

Hamburg, K., Haque, C. E., & Everitt, J. (1997). Municipal waste recycling in Branton, Manitoba: Determinants of participatory behaviour. *Canadian Geographer, 41*(2), 149-165.

Hamed, M. M., Khalafallah, M. G., & Hassanien, E. A. (2004). Prediction of Wastewater Treatment Plant Performance using Artificial Neural Networks. *Environmental Modelling & Software*. http://www.elsevier.com/locate/envsoft

Hockett, D., Lober, D., & Pilgrim, K. (1995). Determinants of Per Capita Municipal Solid Waste Generation in the Southeastern United States. *Journal of Environmental Management, 45*, 205-217.

Hong, S., Adams, R., & Love, A. (1993). An Economic Analysis of Household Recycling of Solid Wastes: The Case Study of Portland, Oregon. *Journal of Environmental Economics and Management, 25*(2), 136-146.

Hong, Y.-S., Rosen, M., & Bhamidimarri, R. (2003). Analysis of a Municipal Wastewater Treatment Plant using a Neural Network-based Pattern Analysis. *Water Research, 37*, 1608-1618.

Instituto del Medio Ambiente Gylania. (2001). *Reciclando en la Comuna (Recycling in the Commune)*. Santiago de Chile: Gylania.

Instituto Nacional de Estadísticas - INE. (1992a). *Censo 1992 (Census 1992)*. Santiago de Chile: INE.

Instituto Nacional de Estadísticas - INE. (1992b). *Ciudades, Pueblos y Aldeas. Chile, Censo 1992 (Cities, Towns and Villages. Chile, Census 1992)*. Santiago de Chile: INE.

Instituto Nacional de Estadísticas - INE. (1998a). *Proyección de Población para 1999 por Sexo y Edades Quinquenales, según Región, Provincia y Comuna (Projection of Population for 1999 per Gender and Quinquennial Ages, according to Region, Province and Commune)*. Santiago de Chile: INE.

Instituto Nacional de Estadísticas - INE. (1998b). *Edificación Aprobada, Sectores Privado y Publico, Obras Nuevas por Destino y Superficie, según Región, Provincia y Comuna, 1998 (Approved Buildings, Private and Public Sectors, New Buildings per Destination and Area, according to Region, Province and Commune, 1998)*. Santiago de Chile: INE.

Instituto Nacional de Estadísticas - INE. (1998c). *Anuario de Cultura y Medios de Comunicación (Culture and Media Yearly Book)*. Santiago de Chile: INE.

Instituto Nacional de Estadísticas - INE. (1999). Parque de Vehículos en Circulación 1999 (Vehicles in Circulation 1999). Santiago de Chile: INE.

Instituto Nacional de Estadísticas - INE. (2001a). *Compendio Estadístico 2001 (Statistical Summary 2001)*. Santiago de Chile: INE.

Instituto Nacional de Estadísticas - INE. (2001b). *CHILE: División Político-Administrativa y Censal 2001 (CHILE: Politic-Administrative and Census Division 2001)*. Santiago de Chile: INE.

Instituto Nacional de Estadísticas - INE. (2002). Encuesta Nacional de Empleo (National Employment Survey). Santiago de Chile: INE.

Instituto Nacional de Estadísticas - INE. (2003). *Censo 2002 (Census 2002)*. Santiago de Chile: Empresa Periodística La Nación S.A.

Instituto Nacional de Estadísticas - INE. Proyección de Población para 1999 por Edades, según comuna (Estimates of Population for 1999 per age and commune). Santiago de Chile: INE.

Jain, A., Mao, J., & Mohiuddin, K. (1996). Artificial Neural Networks: A Tutorial. *Computer*, 31-44.

Johannessen, L. M., & Boyer, G. (1999). *Observations of Solid Waste Landfills in Developing Countries: Africa, Asia, and Latin America.* Washington D.C.: Urban Development Division. Waste Management Anchor Team. The World Bank.

Kerzee, R., Cailas, M., & Swager, R. (1994, Jan 1, 1994). Using Demographics to Predict Future Waste. *Waste Age*.

Kohonen, T. (1998). The self-organizing map. *Neurocomputing, 21*, 1-6.

Koushki, P. A., & Al-Khaleefi, A. L. (1998). An Analysis of Household Solid Waste in Kuwait: Magnitude, Type, and Forecasting Models. *Journal of Air & Waste Management Association, 48*, 256-263.

Lee, M. (Semester 1, 2003). *Multicollinearity*. Lincoln: Commerce Division.

Li, X. M., Zeng, G. M., Wang, M., & Liu, J. J. (2003). Prediction of the Amount of Urban Waste Solids by Applying a Gray Theoretical Model. *Journal of Environmental Sciences-China, 15*(1), 43-46.

Lippmann, R. (1988). An Introduction to Computing with Neural Nets. In V. Vemuri (Ed.), *Neural Networks. ANN: Theoretical Concepts*: Computer Society Press Technology Series.

Maddala, G. (2002). *Introduction to Econometrics*. West Sussex: John Wiley & Sons Ltd.

Mainieri, T., Barnett, E., Valdero, T., Unipan, J., & Oskamp, S. (1997). Green buying: The influence of environmental concern of consumer behavior. *The Journal of Social Psychology, 137*(2), 189-204.

Margai, F. (1997). Analyzing Changes in Waste Reduction Behavior in a Low-Income Urban Community Following a Public Outreach Program. *Environment and Behavior, 29*(6), 769-792.

McBean, E., & Fortin, M. (1993). A Forecast Model of Refuse Tonnage with Recapture and Uncertainty Bounds. *Waste Management & Research, 11*, 373-385.

Ministerio de Planificación - MIDEPLAN, & Banco Interamericano de Desarrollo - BID. (1999). Residuos Sólidos: Estudios y Planes de Manejo. Volumen 3 (Solid Residues: Studies and Management Plans. Volume 3). Santiago de Chile: MIDEPLAN.

Ministerio de Planificación - MIDEPLAN, Banco Interamericano de Desarrollo - BID, KNIGHT PIESOLD S.A. Ingenieros Consultores, & Voight-Weber Ingenieros. (1997). Diagnostico y Manejo de RS para las comunas de San Vicente, Peumo, Pichidegua y Las Cabras. Pre-Informe Final. (Diagnostic and Management of SR for the communes of San Vicente, Peumo, Pichidegua and Las Cabras. Pre-final report). Santiago de Chile: MIDEPLAN.

Ministerio de Planificación - MIDEPLAN. (1998). Encuesta CASEN (CASEN Survey). Santiago de Chile: MIDEPLAN.

Ministerio de Planificación - MIDEPLAN. (2002). Exportaciones según Región 1990-2001 (Exports per Region 1990-2001). Santiago de Chile: MIDEPLAN.

Nagelhout, D., Joosten, M., & Wieringa, K. (1990). Future Waste Disposal in The Netherlands. *Resources, Conservation and Recycling, 4*, 283-295.

Navarro-Esbrí, J., Diamadopoulos, E., & Ginestar, D. (2002). Time series analysis and forecasting techniques for municipal solid waste management. *Resources, Conservation and Recycling, 35*(3), 201-214.

Niessen, W. R. (1977). Estimation of Solid-Waste-Production Rates. In *Handbook of Solid Waste Management* (D.G. Wilson ed., Vol. 14, pp. 544-574). New York, U.S.A.: Van Nostrand Reinhold Co.

Orccosupa, J., Arellano, J., & Figueroa, E. (2002). *Relación entre la producción per capita de residuos sólidos domiciliarios y factores socioeconómicos.* Universidad de Chile.

Oxford Modern English Dictionary. (1996). In (Second ed.). Bungay, Suffolk: Oxford University Press.

Pham, D., & Liu, X. (1995). *Neural Networks for Identification, Prediction and Control.* London: Springer-Verlag.

Rachdawong, P., Khaodhiar, S., & Sangiampaisalsuk, N. (2000). Analysis of solid waste generation. Characteristics in Bangkok, Thailand. *Journal of Environmental Research, 22*(1), 80-92.

Scott, D. (1999). Equal opportunity, unequal results. *Environment and Behavior, 31*(2), 267-290.

Servicio de Salud Metropolitano del Ambiente - SESMA. (2002). *Residuos Domiciliarios (Domestic Waste).* Santiago de Chile: SESMA.

Shell, R. L., & Shupe, D. S. (1972). A Study of The Problems of Predicting Future Volume of Wastes. *Solid Waste Management/RRJ, 15*(3), 38.

Smith, M. (1996). *Neural Networks for Statistical Modelling.* London: International Thomson Computer Press.

Strange, W. (2004). Book Review, City: Urbanism And Its End, by Douglas W. Rae. *Regional Science & Urban Economics.* http://www.elsevier.com/locate/econbase

SystemAnalysis. (1998, May 12, 2003). *Municipal Solid Waste Generation. An Analysis,* from http://www.geocities.com/ResearchTriangle/Thinktank/1036/W/waste.html

United Nations Development Programme - UNDP. (1990). *Human Development Report 1990.* New York, USA: Oxford University Press, Inc.

United Nations Development Programme - UNDP. (2002). *Human Development Report 2002.* New York, USA: Oxford University Press, Inc.

United Nations Development Programme - UNDP. (2004). *Human Development Report 2004.* New York, USA: Oxford University Press, Inc.

United States Environmental Protection Agency - USEPA. (1997). *Adjusting Waste Generation. Appendix H: Methodology to calculate waste generation based on previous years.*

Velásquez, G. (2001). Uso de Instrumentos Económicos para la Gestión de los Residuos Sólidos Domiciliarios en Santiago de Chile. Tesis Magíster en Ciencias de la Ingeniería Industrial. Universidad de Chile. (Use of Economic Instruments to Manage DSW in Santiago de Chile. Master of Sciences Thesis in Industrial Engineering. Universidad de Chile).

West Virginia Management Board. (2003). *West Virginia 2003 - Solid Waste Management Plan.*

Williams, J., & Kulik, A. (1992). America's Attitudes About Recycling. *The American City & County, 107*(8), 48.

World Bank Group. (2001, August 22, 2002). *Chile at a glance.*

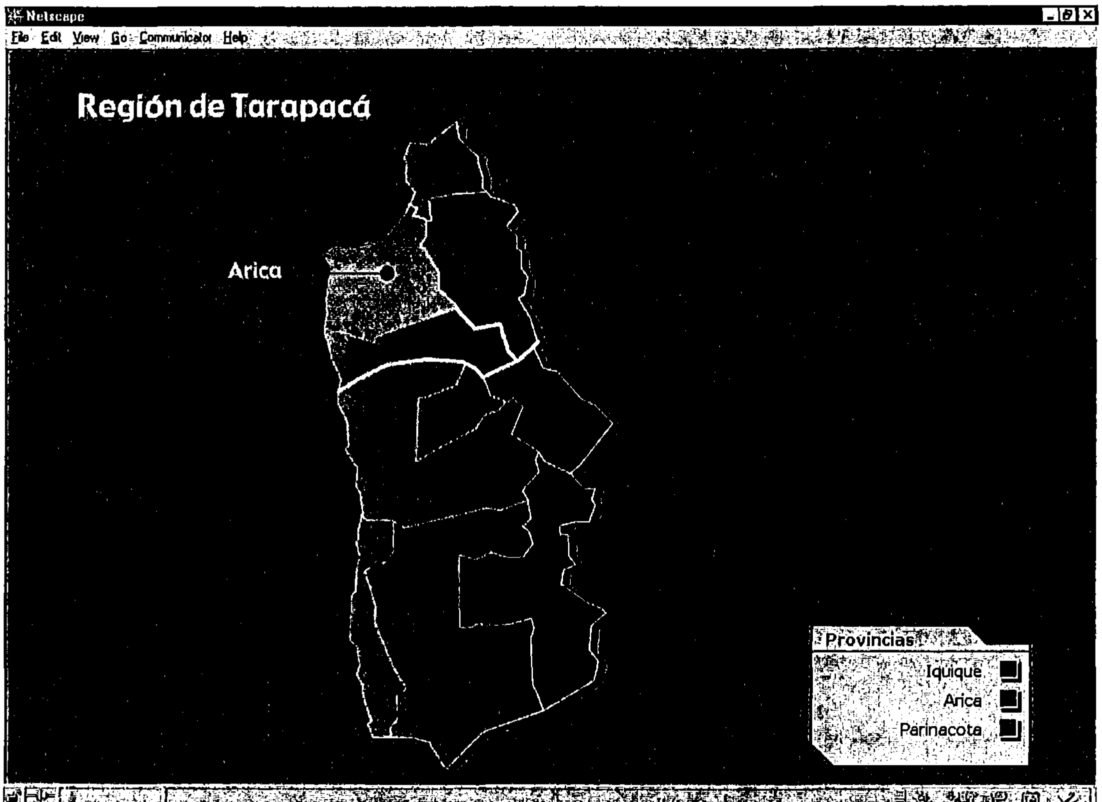
# SOFTWARE

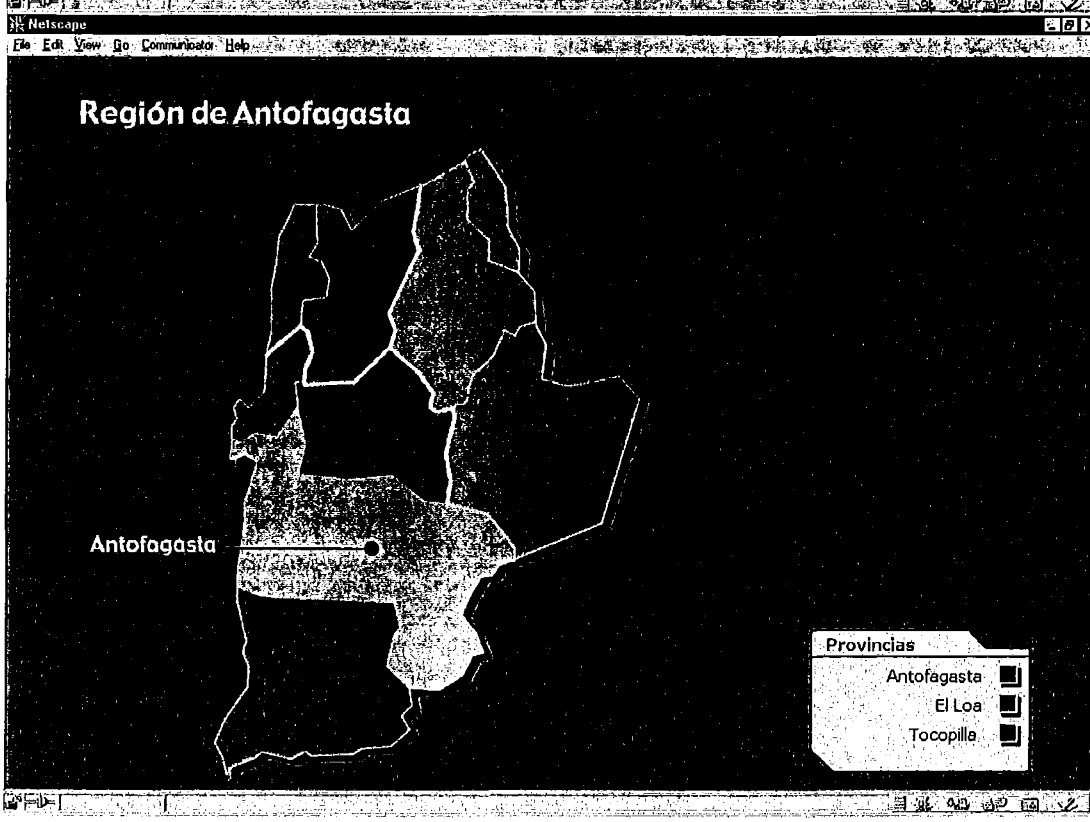
For statistical analysis the software used is SAS – Release 6.12 (1989-1996) by SAS Institute Inc., Cary, NC, USA. Licensed to Lincoln University.

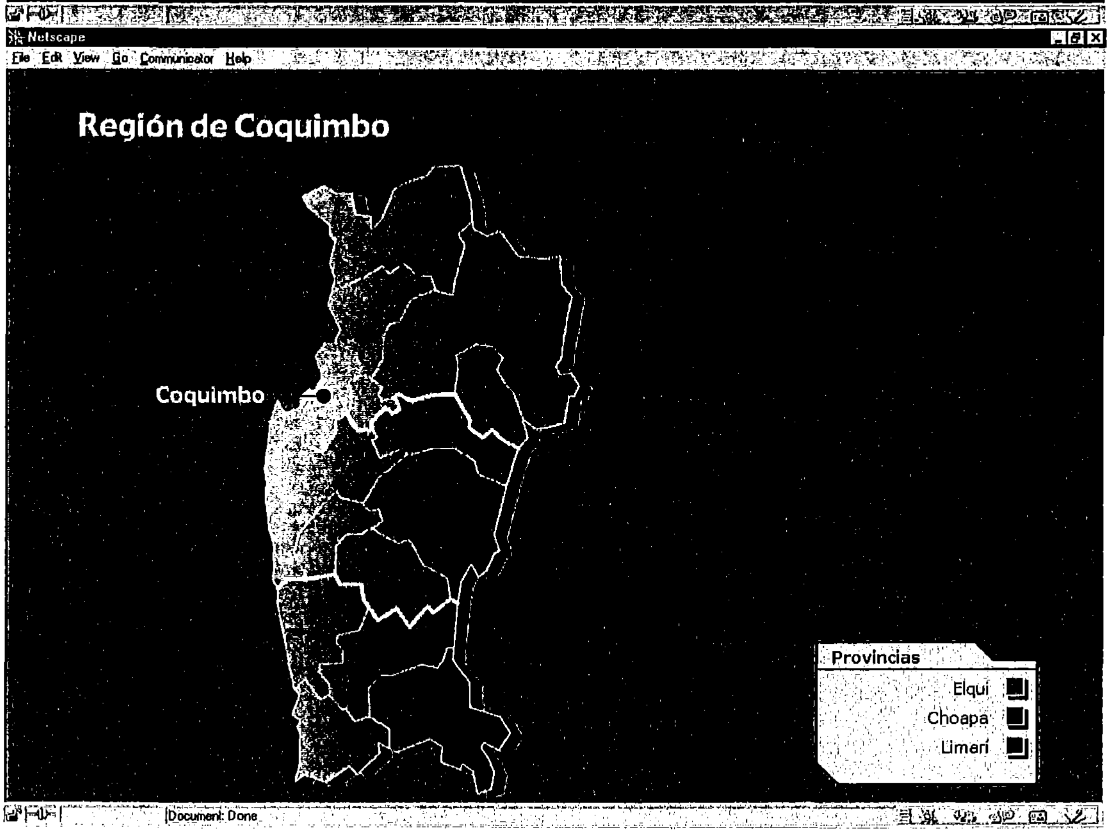
For Neural Networks the software used is NeuroShell 2 – Release 4.0 (1993-1998) by Ward Systems Group®, Inc. Licensed to Lincoln University.

# APPENDIX 1

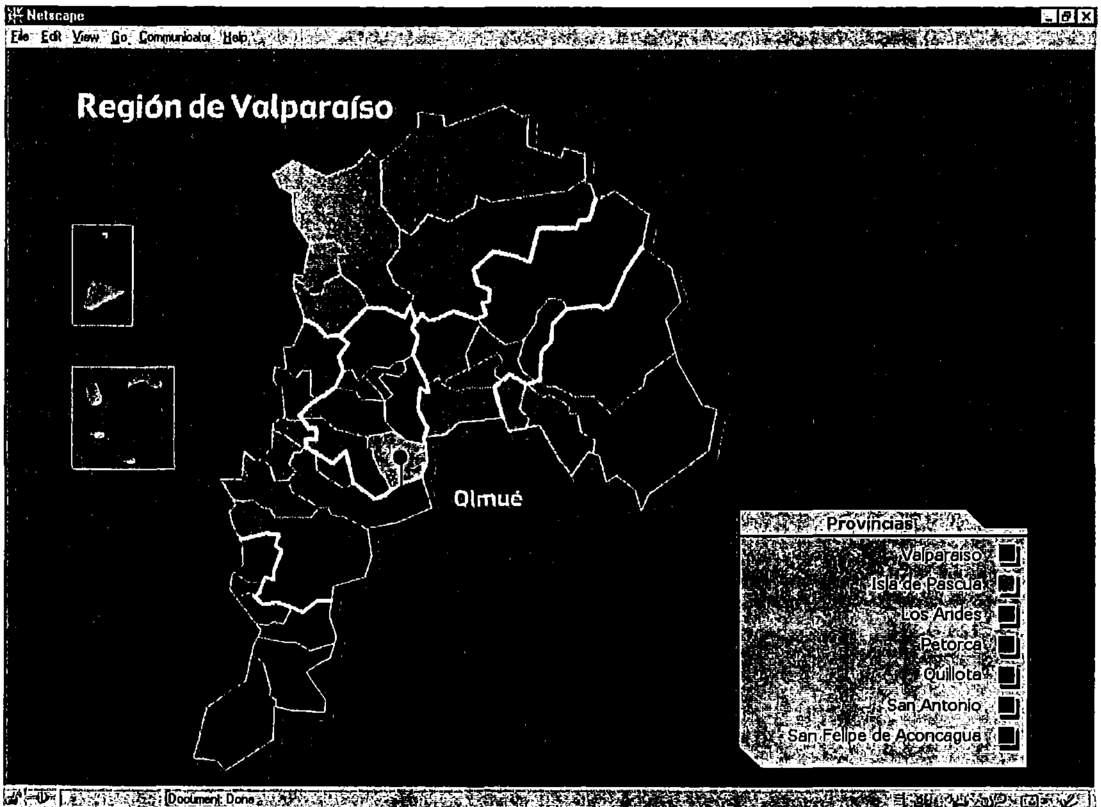
Maps of Regions and Communes of Chile

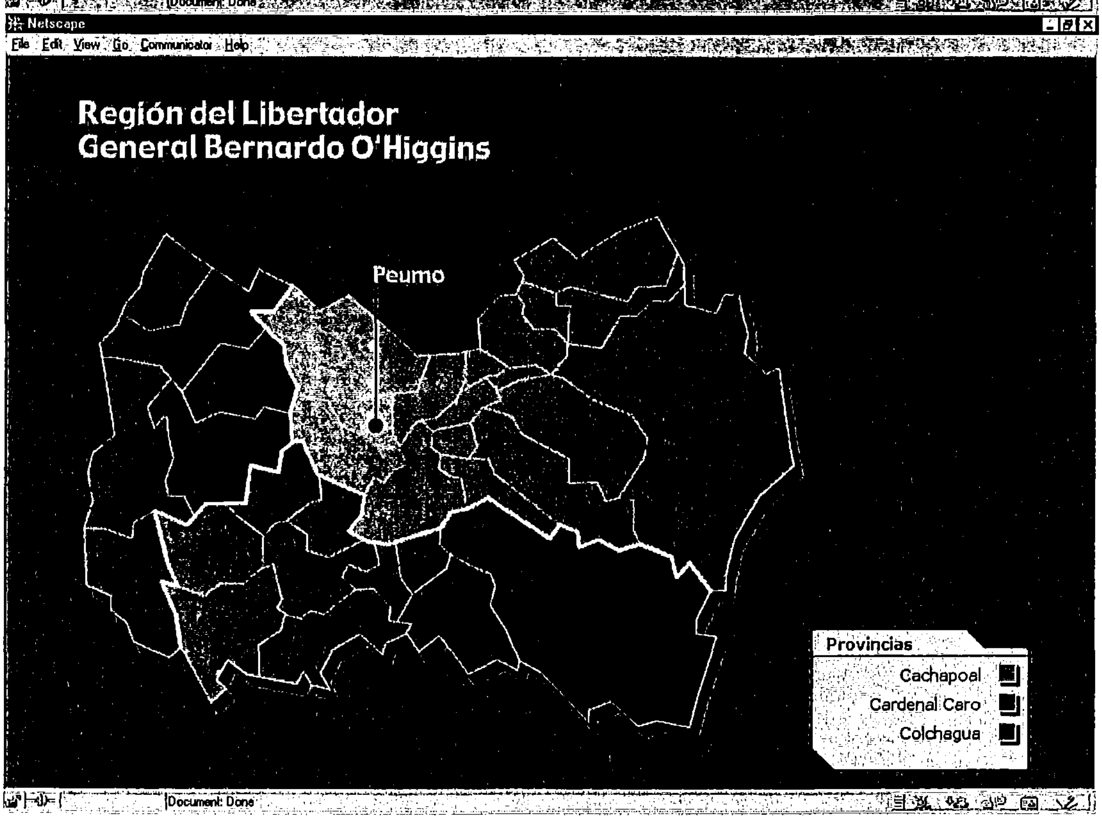


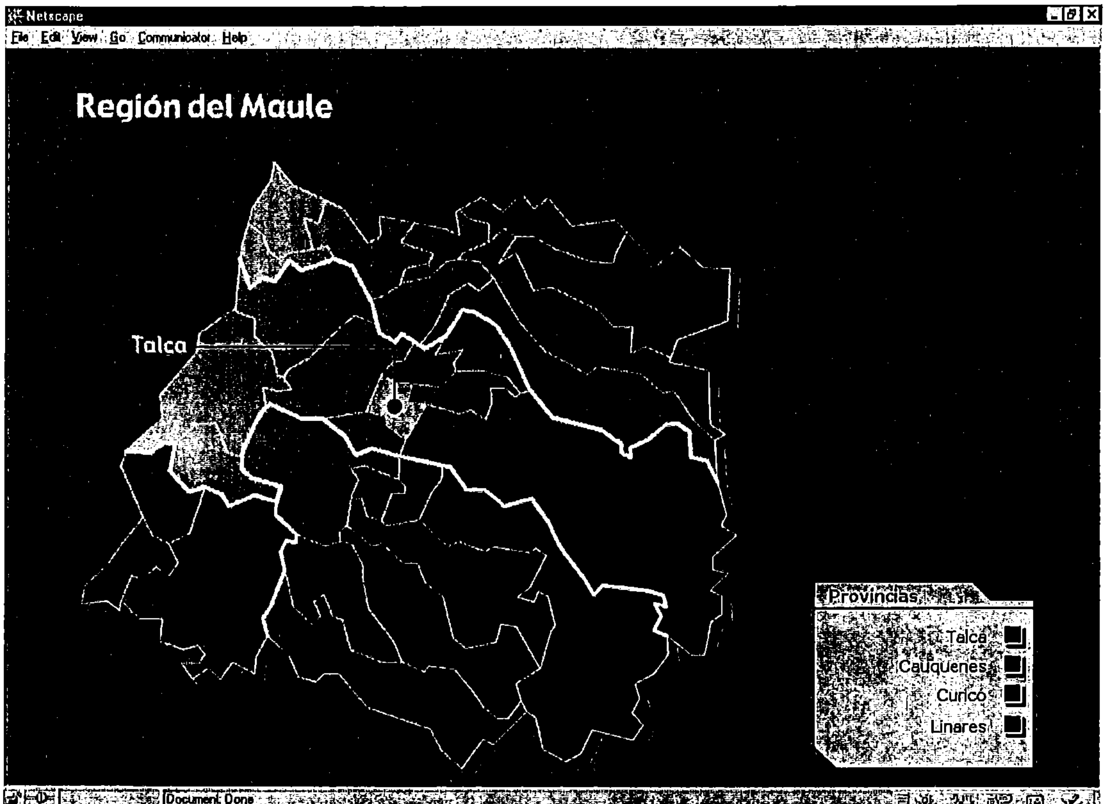



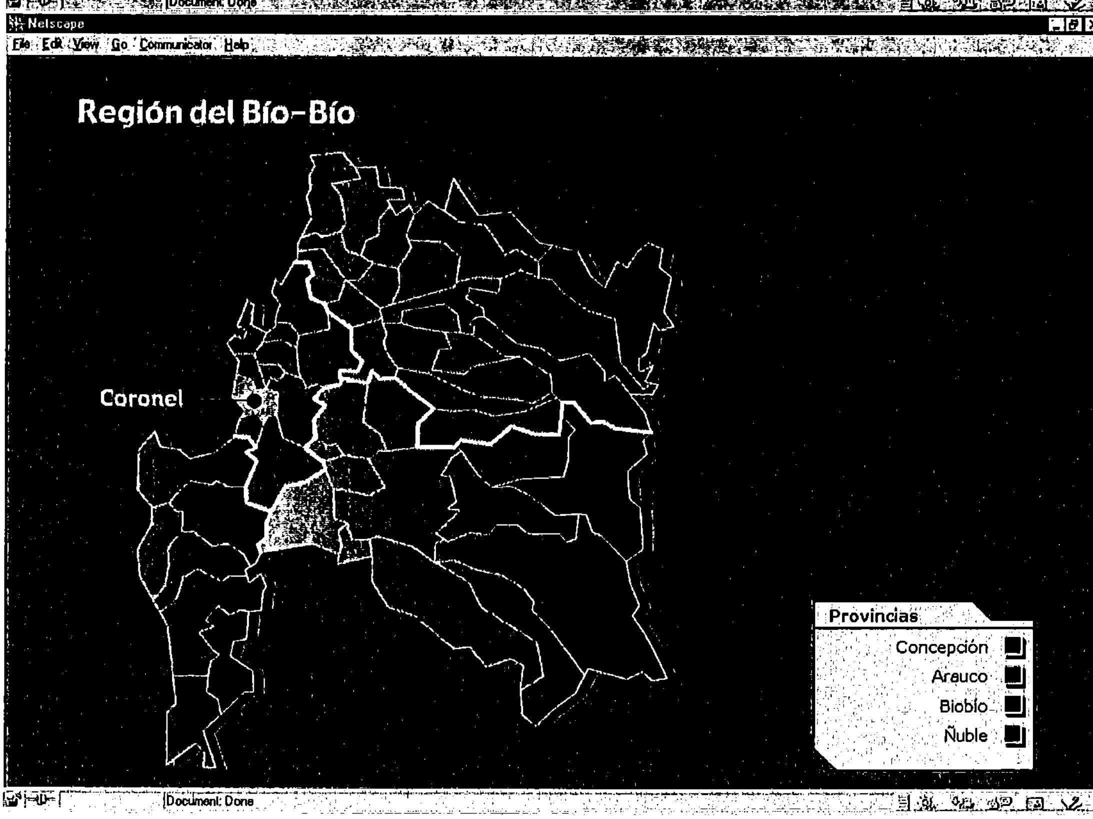

Appendix 1 (cont.)



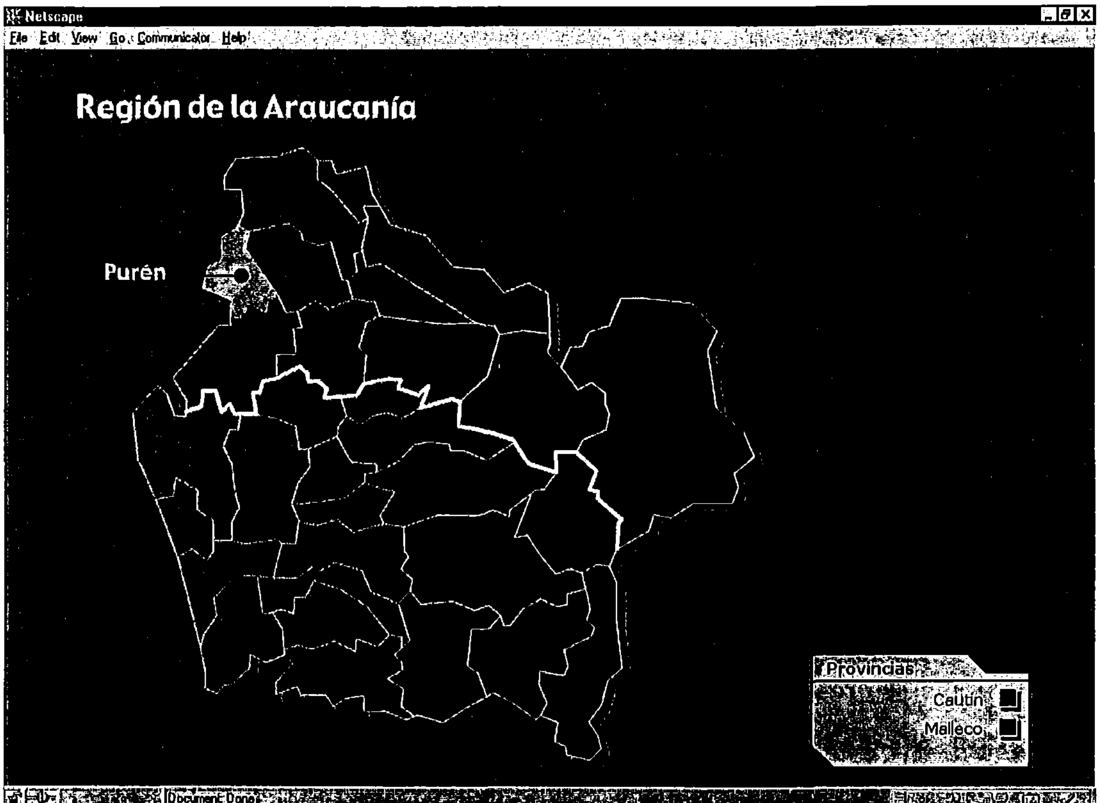



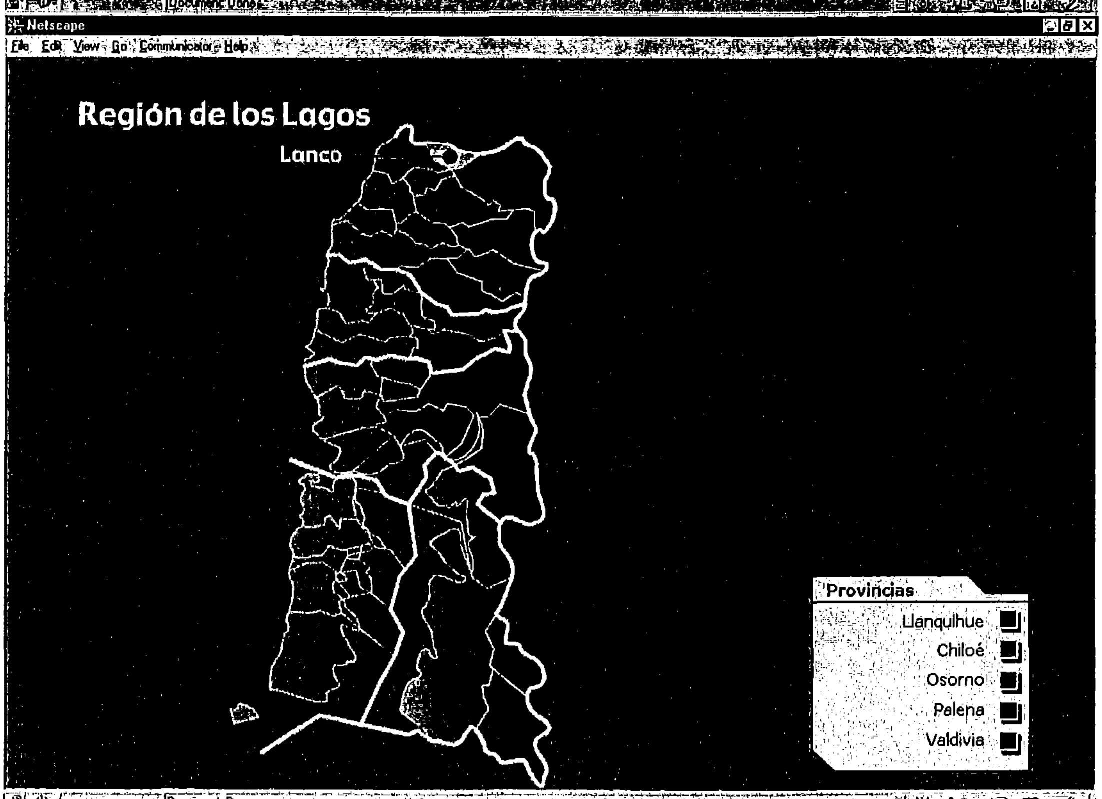

Appendix 1 (cont.)



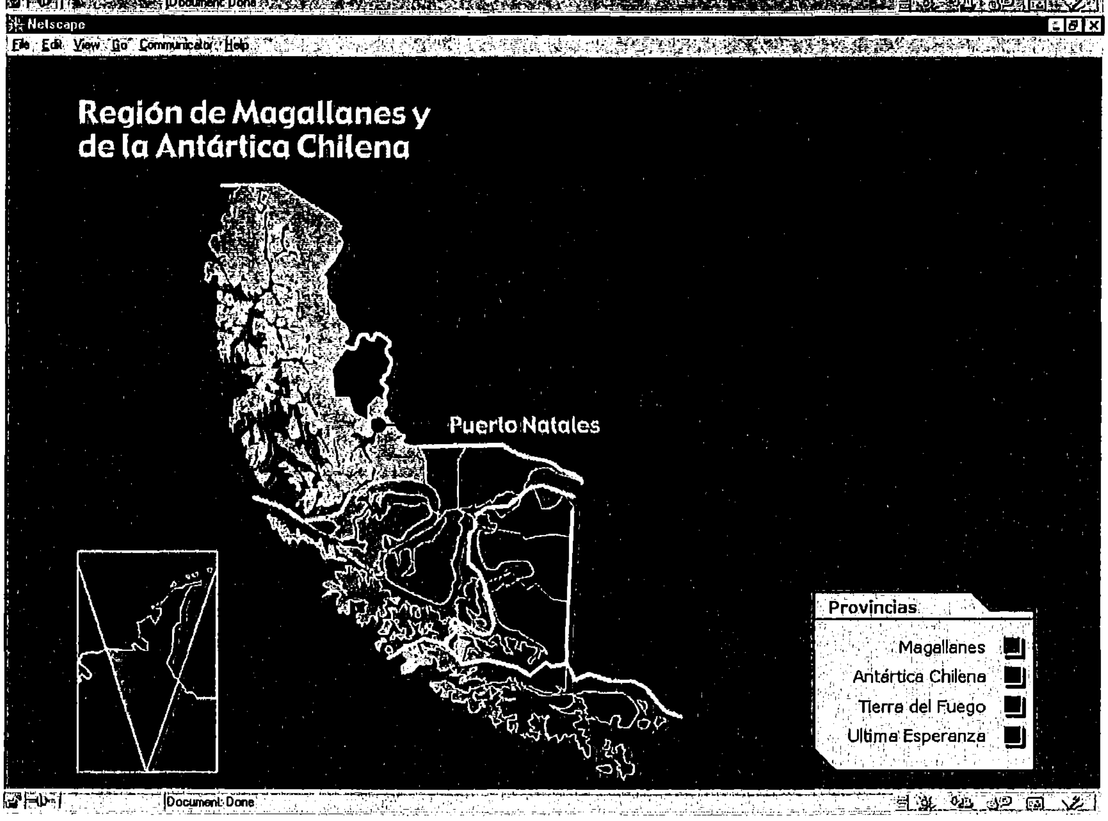




Appendix 1 (cont.)

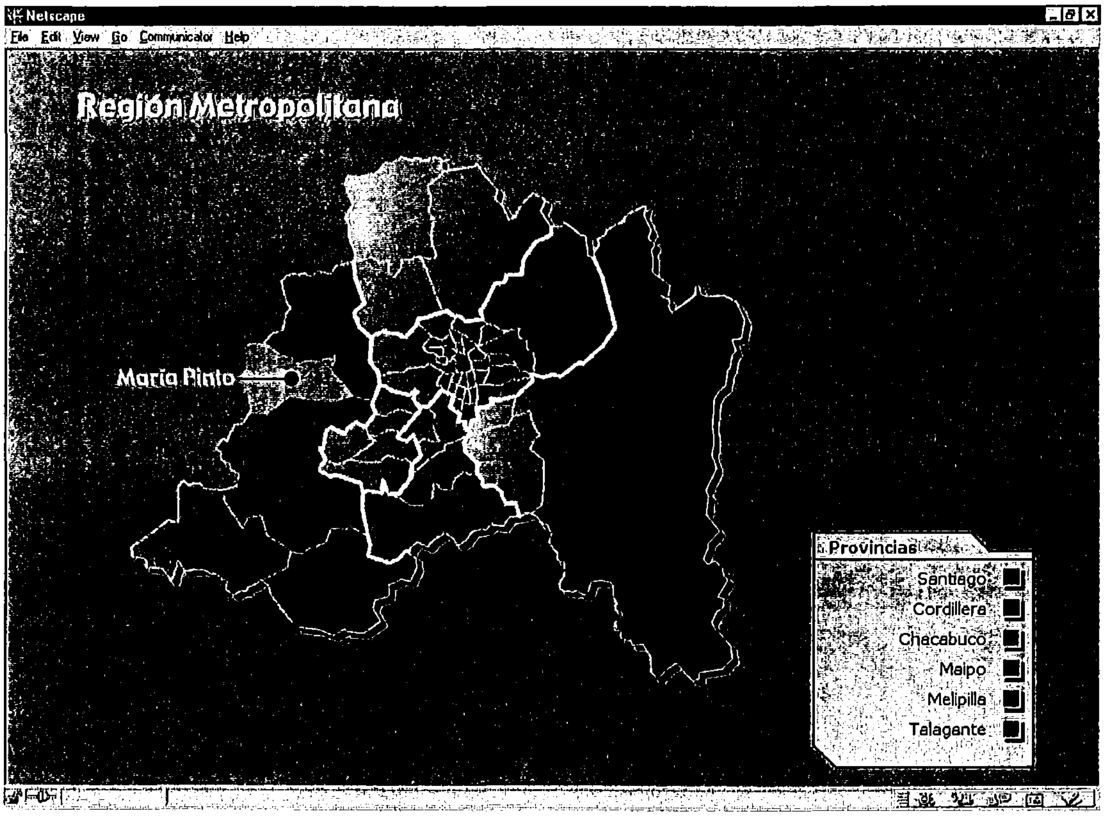



Appendix 1 (cont.)


Appendix 1 (cont.)




Source:
http://www.censo2002.cl

Appendix 1 (cont.)

# APPENDIX 2

Data per Commune

## Table A2.1: Data per Commune



| | | | | | | | | | | AGE GROUPS (5) | | | | | | | | | | | | ECONOMIC ACTIVITY (9) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | POP (1) | AREA (2) | DEN | URB (3) | %URB | MEN (4) | %MEN | 0-14 | 15-24 | 25-44 | 45-64 | 65+ | NAT (6) | IND (7) | %IND | PNI (7) | %PNI | NP (7) | %NP | INC (8) | Tra | Min | Agr-Sil | Man | GDP (10) |
| Arica | 185,268 | 4,799 | 38.6 | 175,441 | 94.70% | 91,742 | 49.52% | 54,035 | 32,693 | 59,060 | 34,538 | 11,115 | 7.46% | 11,511 | 6.26 | 26,804 | 14.58 | 145,535 | 79.16 | 754.05 | 1 | 0 | 0 | 0 | 3.61% |
| General Lagos | 1,179 | 2,244 | 0.5 | 0 | 0.00% | 761 | 64.55% | 279 | 148 | 264 | 235 | 78 | 7.46% | 74 | 7.23 | 112 | 10.94 | 838 | 81.84 | 439.21 | 1 | 0 | 0 | 0 | 3.61% |
| Putre | 1,977 | 5,903 | 0.3 | 1,235 | 62.47% | 1,345 | 68.03% | 440 | 518 | 845 | 553 | 265 | 7.46% | 144 | 9.80 | 133 | 9.05 | 1,192 | 81.14 | 593.31 | 1 | 0 | 0 | 0 | 3.61% |
| Camarones | 1,220 | 3,927 | 0.3 | 0 | 0.00% | 745 | 61.07% | 150 | 112 | 380 | 231 | 82 | 7.46% | 82 | 14.02 | 80 | 13.68 | 423 | 72.31 | 427.08 | 1 | 0 | 0 | 0 | 3.61% |
| Huara | 2,599 | 10,475 | 0.2 | 0 | 0.00% | 1,499 | 57.68% | 463 | 305 | 536 | 376 | 285 | 7.46% | 86 | 5.30 | 243 | 14.96 | 1,295 | 79.74 | 649.64 | 1 | 0 | 0 | 0 | 3.61% |
| Camiña | 1,275 | 2,200 | 0.6 | 0 | 0.00% | 676 | 53.02% | 475 | 229 | 351 | 245 | 116 | 7.46% | 206 | 14.59 | 319 | 22.59 | 887 | 62.82 | 399.72 | 1 | 0 | 0 | 0 | 3.61% |
| Colchane | 1,649 | 4,016 | 0.4 | 0 | 0.00% | 910 | 55.18% | 732 | 300 | 305 | 246 | 124 | 7.46% | 359 | 22.52 | 310 | 19.45 | 925 | 58.03 | 428.07 | 1 | 0 | 0 | 0 | 3.61% |
| Iquique | 216,419 | 2,835 | 76.3 | 214,586 | 99.15% | 108,897 | 50.32% | 51,824 | 31,639 | 58,745 | 29,917 | 9,659 | 7.46% | 2,413 | 1.38 | 15,886 | 9.10 | 156,275 | 89.52 | 1,190.86 | 1 | 0 | 0 | 0 | 3.61% |
| Pozo Almonte | 10,830 | 13,766 | 0.8 | 7,202 | 66.50% | 6,521 | 60.21% | 2,238 | 1,295 | 1,851 | 1,130 | 491 | 7.46% | 213 | 3.28 | 729 | 11.23 | 5,551 | 85.49 | 739.70 | 1 | 0 | 0 | 0 | 3.61% |
| Pica | 6,178 | 8,934 | 0.7 | 4,674 | 75.66% | 4,569 | 73.96% | 674 | 325 | 832 | 569 | 327 | 7.46% | 84 | 3.45 | 406 | 16.66 | 1,947 | 79.89 | 779.60 | 1 | 0 | 0 | 0 | 3.61% |
| Tocopilla | 23,986 | 4,039 | 5.9 | 23,352 | 97.36% | 12,050 | 50.24% | 9,320 | 4,843 | 9,055 | 4,955 | 1,904 | 4.05% | 2,868 | 9.78 | 4,584 | 15.62 | 21,888 | 74.60 | 722.22 | 0 | 1 | 0 | 0 | 8.81% |
| María Elena | 7,530 | 12,197 | 0.6 | 7,412 | 98.43% | 4,298 | 57.08% | 4,157 | 2,071 | 4,824 | 1,798 | 246 | 4.05% | 210 | 2.79 | 777 | 10.32 | 6,543 | 86.89 | 874.27 | 0 | 1 | 0 | 0 | 8.81% |
| Calama | 138,402 | 15,597 | 8.9 | 136,600 | 98.70% | 70,832 | 51.18% | 42,676 | 24,170 | 43,853 | 22,980 | 5,679 | 4.05% | 6,111 | 4.53 | 17,800 | 13.18 | 111,133 | 82.29 | 1,098.18 | 0 | 1 | 0 | 0 | 8.81% |
| Ollagüe | 318 | 2,964 | 0.1 | 0 | 0.00% | 210 | 66.04% | 83 | 57 | 183 | 91 | 17 | 4.05% | 9 | 2.79 | 33 | 10.32 | 276 | 86.89 | 874.27 | 0 | 1 | 0 | 0 | 8.81% |
| Mejillones | 8,418 | 3,804 | 2.2 | 7,888 | 93.70% | 4,654 | 55.29% | 2,393 | 1,297 | 2,793 | 1,092 | 338 | 4.05% | 320 | 4.95 | 990 | 15.31 | 5,156 | 79.74 | 897.22 | 0 | 1 | 0 | 0 | 8.81% |
| Sierra Gorda | 2,356 | 12,886 | 0.2 | 0 | 0.00% | 1,791 | 76.02% | 304 | 141 | 582 | 347 | 72 | 4.05% | 66 | 2.79 | 243 | 10.32 | 2,047 | 86.89 | 874.27 | 0 | 1 | 0 | 0 | 8.81% |
| San Pedro de Atacama | 4,969 | 23,439 | 0.2 | 1,938 | 39.00% | 2,928 | 58.93% | 852 | 453 | 777 | 655 | 333 | 4.05% | 97 | 3.61 | 271 | 10.07 | 2,322 | 86.32 | 664.21 | 0 | 1 | 0 | 0 | 8.81% |
| Antofagasta | 296,905 | 30,718 | 9.7 | 295,792 | 99.63% | 153,220 | 51.61% | 71,273 | 43,088 | 79,148 | 44,708 | 16,513 | 4.05% | 1,501 | 0.62 | 18,483 | 7.61 | 222,861 | 91.77 | 1,217.85 | 0 | 1 | 0 | 0 | 8.81% |
| Taltal | 11,100 | 20,405 | 0.5 | 9,564 | 86.16% | 6,182 | 55.69% | 3,463 | 1,895 | 3,908 | 2,148 | 751 | 4.05% | 991 | 9.96 | 1,889 | 18.99 | 7,066 | 71.04 | 645.95 | 0 | 1 | 0 | 0 | 8.81% |
| Chañaral | 13,543 | 5,772 | 2.3 | 13,180 | 97.32% | 6,968 | 51.45% | 4,491 | 2,539 | 4,470 | 2,426 | 930 | 3.61% | 1,069 | 7.82 | 4,654 | 34.04 | 7,950 | 58.14 | 494.59 | 0 | 1 | 0 | 0 | 2.57% |
| Diego de Almagro | 18,589 | 18,664 | 1.0 | 17,674 | 95.08% | 10,031 | 53.96% | 8,153 | 4,542 | 9,369 | 5,439 | 1,057 | 3.61% | 2,440 | 8.98 | 2,816 | 10.37 | 21,902 | 80.65 | 940.98 | 0 | 1 | 0 | 0 | 2.57% |
| Caldera | 13,734 | 4,667 | 2.9 | 13,540 | 98.59% | 7,237 | 52.69% | 5,371 | 2,884 | 5,754 | 2,439 | 701 | 3.61% | 923 | 5.76 | 3,481 | 21.73 | 11,613 | 72.50 | 662.79 | 0 | 1 | 0 | 0 | 2.57% |
| Copiapó | 129,091 | 16,681 | 7.7 | 125,983 | 97.59% | 64,922 | 50.29% | 36,352 | 21,413 | 38,849 | 19,442 | 6,707 | 3.61% | 4,963 | 4.24 | 31,061 | 26.52 | 81,108 | 69.24 | 791.79 | 0 | 1 | 0 | 0 | 2.57% |
| Tierra Amarilla | 12,888 | 11,191 | 1.2 | 8,578 | 66.56% | 7,277 | 56.46% | 4,831 | 2,651 | 5,223 | 2,022 | 537 | 3.61% | 1,200 | 8.83 | 3,155 | 23.20 | 9,242 | 67.97 | 727.65 | 0 | 1 | 0 | 0 | 2.57% |
| Huasco | 7,945 | 1,601 | 5.0 | 6,445 | 81.12% | 3,999 | 50.33% | 2,207 | 1,165 | 2,365 | 1,605 | 665 | 3.61% | 399 | 5.13 | 1,122 | 14.44 | 6,251 | 80.43 | 698.53 | 0 | 1 | 0 | 0 | 2.57% |
| Freirina | 5,666 | 3,578 | 1.6 | 3,469 | 61.22% | 2,800 | 49.42% | 1,922 | 932 | 1,428 | 923 | 415 | 3.61% | 355 | 6.49 | 1,543 | 28.19 | 3,576 | 65.33 | 519.66 | 0 | 1 | 0 | 0 | 2.57% |
| Vallenar | 48,040 | 7,084 | 6.8 | 43,750 | 91.07% | 23,284 | 48.47% | 15,807 | 8,563 | 14,977 | 9,076 | 3,871 | 3.61% | 2,614 | 5.15 | 10,069 | 19.85 | 38,052 | 75.00 | 692.84 | 0 | 1 | 0 | 0 | 2.57% |
| Alto del Carmen | 4,840 | 5,939 | 0.8 | 0 | 0.00% | 2,629 | 54.32% | 1,202 | 645 | 1,210 | 935 | 542 | 3.61% | 183 | 4.25 | 684 | 15.87 | 3,442 | 79.88 | 490.44 | 0 | 1 | 0 | 0 | 2.57% |
| La Higuera | 3,721 | 4,158 | 0.9 | 1,080 | 29.02% | 2,084 | 56.01% | 982 | 599 | 925 | 538 | 225 | 4.16% | 168 | 5.49 | 415 | 13.57 | 2,476 | 80.94 | 503.69 | 0 | 0 | 1 | 0 | 2.65% |
| La Serena | 160,148 | 1,892 | 84.6 | 147,815 | 92.30% | 77,385 | 48.32% | 40,213 | 24,735 | 42,502 | 22,456 | 9,947 | 4.16% | 5,755 | 4.27 | 15,955 | 11.83 | 113,111 | 83.90 | 1,190.41 | 0 | 0 | 1 | 0 | 2.65% |
| Vicuña | 24,010 | 7,610 | 3.2 | 12,910 | 53.77% | 12,302 | 51.24% | 6,268 | 3,584 | 7,199 | 3,731 | 1,709 | 4.16% | 505 | 2.46 | 3,078 | 15.01 | 16,926 | 82.53 | 618.79 | 0 | 0 | 1 | 0 | 2.65% |
| Coquimbo | 163,036 | 1,429 | 114.1 | 154,316 | 94.65% | 79,428 | 48.72% | 43,777 | 25,867 | 44,451 | 23,021 | 9,381 | 4.16% | 8,607 | 6.02 | 24,223 | 16.95 | 110,110 | 77.03 | 774.84 | 0 | 0 | 1 | 0 | 2.65% |
| Andacollo | 10,288 | 310 | 33.2 | 9,444 | 91.80% | 5,148 | 50.04% | 4,366 | 2,113 | 4,494 | 2,116 | 993 | 4.16% | 471 | 3.43 | 4,684 | 34.13 | 8,571 | 62.44 | 443.07 | 0 | 0 | 1 | 0 | 2.65% |
| RíoHurtado | 4,771 | 2,117 | 2.3 | 0 | 0.00% | 2,445 | 51.25% | 1,480 | 809 | 1,312 | 827 | 525 | 4.16% | 312 | 6.60 | 1,399 | 29.60 | 3,016 | 63.80 | 477.52 | 0 | 0 | 1 | 0 | 2.65% |
| Paihuano | 4,168 | 1,495 | 2.8 | 0 | 0.00% | 2,145 | 51.46% | 1,011 | 475 | 1,028 | 632 | 338 | 4.16% | 182 | 5.65 | 240 | 7.45 | 2,800 | 86.90 | 695.51 | 0 | 0 | 1 | 0 | 2.65% |
| Ovalle | 98,089 | 3,835 | 25.6 | 73,790 | 75.23% | 47,805 | 48.74% | 30,210 | 16,750 | 27,501 | 14,751 | 6,983 | 4.16% | 4,950 | 5.30 | 27,829 | 29.79 | 60,637 | 64.91 | 636.15 | 0 | 0 | 1 | 0 | 2.65% |
| Punitaqui | 9,539 | 1,339 | 7.1 | 3,615 | 37.90% | 4,791 | 50.23% | 2,881 | 1,507 | 2,547 | 1,668 | 821 | 4.16% | 1,406 | 15.82 | 1,544 | 17.37 | 5,939 | 66.81 | 525.49 | 0 | 0 | 1 | 0 | 2.65% |
| Monte Patria | 30,276 | 4,366 | 6.9 | 13,340 | 44.06% | 15,351 | 50.70% | 9,873 | 5,265 | 9,156 | 4,532 | 2,153 | 4.16% | 2,573 | 8.57 | 5,410 | 18.02 | 22,037 | 73.41 | 414.47 | 0 | 0 | 1 | 0 | 2.65% |
| Combarbalá | 13,483 | 1,896 | 7.1 | 5,494 | 40.75% | 6,695 | 49.66% | 3,850 | 2,092 | 3,755 | 2,455 | 1,599 | 4.16% | 1,311 | 9.78 | 2,414 | 18.00 | 9,685 | 72.22 | 384.54 | 0 | 0 | 1 | 0 | 2.65% |
| Canela | 9,379 | 2,197 | 4.3 | 1,744 | 18.59% | 4,737 | 50.51% | 3,063 | 1,568 | 2,647 | 1,766 | 1,036 | 4.16% | 1,721 | 17.92 | 2,038 | 21.22 | 5,847 | 60.87 | 393.01 | 0 | 0 | 1 | 0 | 2.65% |
| Illapel | 30,355 | 2,629 | 11.5 | 21,826 | 71.90% | 14,940 | 49.22% | 9,406 | 5,586 | 9,067 | 5,123 | 2,425 | 4.16% | 2,941 | 9.75 | 6,863 | 22.74 | 20,371 | 67.51 | 605.08 | 0 | 0 | 1 | 0 | 2.65% |
| Los Vilos | 17,453 | 1,861 | 9.4 | 12,859 | 73.68% | 8,858 | 50.75% | 5,316 | 2,956 | 5,645 | 3,044 | 1,289 | 4.16% | 1,044 | 6.22 | 3,382 | 20.15 | 12,356 | 73.63 | 588.77 | 0 | 0 | 1 | 0 | 2.65% |
| Salamanca | 24,494 | 3,445 | 7.1 | 12,689 | 51.80% | 13,043 | 53.25% | 7,157 | 4,001 | 7,444 | 4,366 | 1,942 | 4.16% | 2,154 | 9.14 | 3,958 | 16.80 | 17,450 | 74.06 | 501.89 | 0 | 0 | 1 | 0 | 2.65% |
| La Ligua | 31,987 | 1,163 | 27.5 | 24,214 | 75.70% | 16,079 | 50.27% | 9,010 | 4,932 | 10,427 | 5,615 | 2,191 | 4.71% | 1,760 | 5.59 | 7,575 | 24.08 | 22,129 | 70.33 | 715.75 | 0 | 0 | 0 | 1 | 8.38% |
| Petorca | 9,440 | 1,517 | 6.2 | 4,535 | 48.04% | 4,806 | 50.91% | 2,679 | 1,442 | 3,040 | 1,669 | 823 | 4.71% | 480 | 5.03 | 1,768 | 18.54 | 7,287 | 76.42 | 504.99 | 0 | 0 | 0 | 1 | 8.38% |
| Cabildo | 18,916 | 1,455 | 13.0 | 12,453 | 65.83% | 9,466 | 50.04% | 6,375 | 3,238 | 6,477 | 3,196 | 1,153 | 4.71% | 1,424 | 7.21 | 3,395 | 17.20 | 14,920 | 75.59 | 577.47 | 0 | 0 | 0 | 1 | 8.38% |
| Putaendo | 14,649 | 1,474 | 9.9 | 7,214 | 49.25% | 7,344 | 50.13% | 3,785 | 2,000 | 4,059 | 2,503 | 1,364 | 4.71% | 811 | 6.15 | 2,542 | 19.27 | 9,837 | 74.58 | 520.51 | 0 | 0 | 0 | 1 | 8.38% |
| San Esteban | 14,400 | 1,362 | 10.6 | 7,542 | 52.38% | 7,298 | 50.68% | 3,300 | 2,190 | 4,386 | 2,367 | 981 | 4.71% | 956 | 7.25 | 2,138 | 16.22 | 10,084 | 76.52 | 608.55 | 0 | 0 | 0 | 1 | 8.38% |
| Los Andes | 60,198 | 1,248 | 48.2 | 55,388 | 92.01% | 30,247 | 50.25% | 15,548 | 9,263 | 18,454 | 10,649 | 3,813 | 4.71% | 0 | 0.00 | 8,130 | 14.74 | 47,018 | 85.26 | 876.37 | 0 | 0 | 0 | 1 | 8.38% |
| Papudo | 4,608 | 166 | 27.8 | 4,343 | 94.25% | 2,382 | 51.69% | 1,083 | 710 | 1,288 | 774 | 418 | 4.71% | 291 | 7.45 | 1,019 | 26.10 | 2,594 | 66.44 | 540.81 | 0 | 0 | 0 | 1 | 8.38% |
| Zapallar | 5,659 | 288 | 19.6 | 4,744 | 83.83% | 2,914 | 51.49% | 1,264 | 756 | 1,654 | 971 | 476 | 4.71% | 0 | 0.00 | 559 | 11.19 | 4,436 | 88.81 | 753.34 | 0 | 0 | 0 | 1 | 8.38% |
| Puchuncaví | 12,954 | 300 | 43.2 | 11,099 | 85.68% | 6,643 | 51.28% | 3,404 | 1,713 | 3,989 | 2,453 | 1,203 | 4.71% | 1,498 | 11.99 | 2,709 | 21.69 | 8,283 | 66.32 | 460.09 | 0 | 0 | 0 | 1 | 8.38% |
| Nogales | 21,633 | 405 | 53.4 | 18,698 | 86.43% | 10,786 | 49.86% | 6,048 | 3,368 | 6,580 | 3,474 | 1,420 | 4.71% | 1,857 | 9.04 | 3,183 | 15.50 | 15,495 | 75.46 | 602.34 | 0 | 0 | 0 | 1 | 8.38% |
| Catemu | 12,112 | 362 | 33.5 | 6,706 | 55.37% | 6,172 | 50.96% | 3,720 | 2,006 | 3,680 | 2,062 | 816 | 4.71% | 412 | 3.40 | 2,782 | 22.99 | 8,908 | 73.61 | 528.85 | 0 | 0 | 0 | 1 | 8.38% |
| San Felipe | 64,126 | 186 | 344.9 | 57,760 | 90.07% | 31,036 | 48.40% | 18,609 | 10,471 | 19,926 | 10,481 | 4,418 | 4.71% | 0 | 0.00 | 13,407 | 21.64 | 48,557 | 78.36 | 757.42 | 0 | 0 | 0 | 1 | 8.38% |
| Santa María | 12,813 | 166 | 77.0 | 8,126 | 63.42% | 6,427 | 50.16% | 3,820 | 2,228 | 4,081 | 2,241 | 966 | 4.71% | 672 | 5.09 | 2,244 | 16.98 | 10,299 | 77.93 | 605.91 | 0 | 0 | 0 | 1 | 8.38% |
| Quintero | 21,174 | 148 | 143.6 | 18,719 | 88.41% | 10,390 | 49.07% | 5,566 | 3,209 | 6,334 | 3,629 | 1,713 | 4.71% | 1,266 | 6.46 | 2,062 | 10.52 | 16,274 | 83.02 | 687.26 | 0 | 0 | 0 | 1 | 8.38% |
| La Cruz | 12,851 | 78 | 164.3 | 10,611 | 82.57% | 6,348 | 49.40% | 3,258 | 1,766 | 3,506 | 2,158 | 1,051 | 4.71% | 0 | 0.00 | 2,295 | 19.79 | 9,303 | 80.21 | 919.49 | 0 | 0 | 0 | 1 | 8.38% |
| Calera | 49,503 | 61 | 818.2 | 47,836 | 96.63% | 24,134 | 48.75% | 14,048 | 8,283 | 14,957 | 8,658 | 3,747 | 4.71% | 2,383 | 4.86 | 10,172 | 20.75 | 36,466 | 74.39 | 796.46 | 0 | 0 | 0 | 1 | 8.38% |
| Hijuelas | 16,014 | 267 | 59.9 | 8,196 | 51.18% | 8,161 | 50.96% | 4,673 | 2,606 | 4,982 | 2,581 | 1,040 | 4.71% | 845 | 5.39 | 1,775 | 11.32 | 13,054 | 83.28 | 660.58 | 0 | 0 | 0 | 1 | 8.38% |
| Panquehue | 6,567 | 122 | 53.9 | 2,904 | 44.22% | 3,312 | 50.43% | 2,184 | 1,135 | 2,135 | 1,082 | 422 | 4.71% | 472 | 6.75 | 1,104 | 15.79 | 5,416 | 77.46 | 538.96 | 0 | 0 | 0 | 1 | 8.38% |
| Rinconada | 6,692 | 123 | 54.6 | 5,727 | 85.58% | 3,429 | 51.24% | 1,744 | 1,057 | 2,096 | 1,167 | 476 | 4.71% | 515 | 8.06 | 1,487 | 23.28 | 4,385 | 68.66 | 528.56 | 0 | 0 | 0 | 1 | 8.38% |
| Calle Larga | 10,393 | 322 | 32.3 | 5,447 | 52.41% | 5,351 | 51.49% | 2,735 | 1,718 | 3,414 | 1,836 | 756 | 4.71% | 0 | 0.00 | 2,222 | 21.68 | 8,028 | 78.32 | 663.90 | 0 | 0 | 0 | 1 | 8.38% |
| Llaillay | 21,644 | 349 | 62.0 | 16,215 | 74.92% | 10,799 | 49.89% | 6,812 | 3,599 | 6,777 | 3,602 | 1,602 | 4.71% | 1,013 | 4.58 | 3,120 | 14.11 | 17,979 | 81.31 | 619.14 | 0 | 0 | 0 | 1 | 8.38% |
| Quillota | 75,916 | 302 | 251.4 | 66,025 | 86.97% | 37,191 | 48.99% | 20,535 | 11,974 | 21,455 | 13,136 | 6,504 | 4.71% | 0 | 0.00 | 17,376 | 24.20 | 54,428 | 75.80 | 737.91 | 0 | 0 | 0 | 1 | 8.38% |
| Concón | 32,273 | 76 | 424.6 | 31,558 | 97.78% | 15,713 | 48.69% | 8,882 | 5,153 | 9,770 | 5,741 | 2,726 | 4.71% | 0 | 0.00 | 2,711 | 12.16 | 19,586 | 87.84 | 1,767.09 | 0 | 0 | 0 | 1 | 8.38% |

# Table A2.1: Data per Commune

| | | | | | | | | AGE GROUPS (5) | | | | | | | | | | | | | ECONOMIC ACTIVITY (9) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | POP (1) | AREA (2) | DEN | URB (3) | %URB | MEN (4) | %MEN | 0-14 | 15-24 | 25-44 | 45-64 | 65+ | NAT (6) | IND (7) | %IND | PNI (7) | %PNI | NP (7) | %NP | INC (8) | Tra | Min | Agr-Sil | Man | GDP (10) |
| Limache | 39,219 | 294 | 133.5 | 34,948 | 89.11% | 19,269 | 49.13% | 10,987 | 6,199 | 11,532 | 6,824 | 3,644 | 4.71% | 1,465 | 3.87 | 5,994 | 15.82 | 30,430 | 80.31 | 748.92 | 0 | 0 | 0 | 1 | 8.38% |
| Olmué | 14,105 | 232 | 60.8 | 10,379 | 73.58% | 7,139 | 50.61% | 3,927 | 2,176 | 3,866 | 2,386 | 1,277 | 4.71% | 868 | 6.43 | 2,174 | 16.11 | 10,450 | 77.45 | 527.16 | 0 | 0 | 0 | 1 | 8.38% |
| Viña del Mar | 286,931 | 122 | 2,359.6 | 286,931 | 100.00% | 136,318 | 47.51% | 89,892 | 55,857 | 101,983 | 60,979 | 30,771 | 4.71% | 0 | 0.00 | 47,973 | 15.63 | 258,880 | 84.37 | 1,431.52 | 0 | 0 | 0 | 1 | 8.38% |
| Quilpué | 128,578 | 537 | 239.5 | 126,893 | 98.69% | 61,329 | 47.70% | 32,587 | 18,564 | 35,534 | 22,660 | 11,534 | 4.71% | 0 | 0.00 | 10,142 | 8.58 | 108,059 | 91.42 | 1,048.00 | 0 | 0 | 0 | 1 | 8.38% |
| Villa Alemana | 95,623 | 97 | 990.9 | 94,802 | 99.14% | 45,868 | 47.97% | 23,801 | 13,420 | 25,470 | 15,460 | 7,682 | 4.71% | 3,676 | 4.36 | 8,950 | 10.63 | 71,602 | 85.01 | 965.97 | 0 | 0 | 0 | 1 | 8.38% |
| Valparaiso | 275,982 | 402 | 687.2 | 275,141 | 99.70% | 135,217 | 48.99% | 79,579 | 47,029 | 89,288 | 52,807 | 25,803 | 4.71% | 19,166 | 6.71 | 41,637 | 14.57 | 224,981 | 78.72 | 771.15 | 0 | 0 | 0 | 1 | 8.38% |
| Casablanca | 21,874 | 953 | 23.0 | 15,209 | 69.53% | 11,127 | 50.87% | 5,449 | 2,918 | 5,858 | 3,114 | 1,429 | 4.71% | 0 | 0.00 | 3,362 | 18.38 | 14,934 | 81.62 | 751.14 | 0 | 0 | 0 | 1 | 8.38% |
| Algarrobo | 8,601 | 176 | 49.0 | 6,628 | 77.06% | 4,369 | 50.80% | 1,759 | 1,005 | 2,248 | 1,423 | 637 | 4.71% | 0 | 0.00 | 549 | 8.15 | 6,187 | 91.85 | 964.19 | 0 | 0 | 0 | 1 | 8.38% |
| El Quisco | 9,467 | 51 | 186.7 | 8,931 | 94.34% | 4,815 | 50.86% | 2,211 | 1,061 | 2,163 | 1,557 | 860 | 4.71% | 673 | 9.64 | 1,640 | 23.49 | 4,669 | 66.87 | 568.95 | 0 | 0 | 0 | 1 | 8.38% |
| El Tabo | 7,028 | 99 | 71.1 | 6,604 | 93.97% | 3,537 | 50.33% | 1,375 | 778 | 1,505 | 1,250 | 805 | 4.71% | 0 | 0.00 | 1,118 | 21.70 | 4,034 | 78.30 | 521.35 | 0 | 0 | 0 | 1 | 8.38% |
| Cartagena | 16,875 | 246 | 68.6 | 15,302 | 90.68% | 8,396 | 49.75% | 3,538 | 1,894 | 3,704 | 2,819 | 1,523 | 4.71% | 651 | 4.92 | 1,142 | 8.64 | 11,426 | 86.44 | 670.14 | 0 | 0 | 0 | 1 | 8.38% |
| San Antonio | 87,205 | 405 | 215.6 | 83,435 | 95.68% | 42,843 | 49.13% | 26,103 | 14,249 | 26,597 | 14,986 | 6,293 | 4.71% | 4,652 | 5.40 | 12,853 | 14.93 | 68,588 | 79.67 | 714.11 | 0 | 0 | 0 | 1 | 8.38% |
| Santo Domingo | 7,418 | 536 | 13.8 | 4,737 | 63.86% | 3,811 | 51.38% | 2,226 | 1,126 | 2,469 | 1,312 | 585 | 4.71% | 0 | 0.00 | 717 | 9.83 | 6,578 | 90.17 | 1,014.27 | 0 | 0 | 0 | 1 | 8.38% |
| Juan Fernández | 633 | 148 | 4.3 | 598 | 94.47% | 377 | 59.56% | 121 | 60 | 178 | 100 | 26 | 4.71% | 20 | 3.19 | 99 | 15.63 | 514 | 81.18 | 740.79 | 0 | 0 | 0 | 1 | 8.38% |
| Isla de Pascua | 3,791 | 164 | 23.2 | 3,304 | 87.15% | 1,985 | 52.36% | 1,075 | 482 | 1,168 | 625 | 166 | 4.71% | 121 | 3.19 | 592 | 15.63 | 3,077 | 81.18 | 740.79 | 0 | 0 | 0 | 1 | 8.38% |
| Navidad | 5,422 | 300 | 18.0 | 712 | 13.13% | 2,878 | 53.08% | 1,291 | 675 | 1,386 | 1,106 | 707 | 5.46% | 286 | 5.28 | 970 | 17.89 | 4,166 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Litueche | 5,526 | 619 | 8.9 | 2,479 | 44.86% | 2,932 | 53.06% | 1,507 | 859 | 1,709 | 1,070 | 478 | 5.46% | 292 | 5.28 | 989 | 17.89 | 4,246 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Las Cabras | 20,242 | 749 | 27.0 | 7,548 | 37.29% | 10,621 | 52.47% | 5,589 | 3,141 | 6,186 | 3,328 | 1,546 | 5.46% | 1,069 | 5.28 | 3,621 | 17.89 | 15,552 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Coltauco | 16,228 | 225 | 72.2 | 6,958 | 42.88% | 8,239 | 50.77% | 4,682 | 2,824 | 5,074 | 2,743 | 1,306 | 5.46% | 857 | 5.28 | 2,903 | 17.89 | 12,468 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Doñihue | 16,916 | 78 | 216.3 | 15,590 | 92.16% | 8,475 | 50.10% | 4,531 | 2,959 | 4,824 | 2,713 | 1,186 | 5.46% | 893 | 5.28 | 3,026 | 17.89 | 12,997 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Rancagua | 214,344 | 260 | 823.4 | 206,971 | 96.56% | 104,879 | 48.93% | 60,740 | 37,686 | 67,710 | 37,679 | 12,927 | 5.46% | 11,022 | 5.24 | 30,849 | 14.68 | 168,282 | 80.08 | 950.11 | 0 | 0 | 1 | 0 | 4.54% |
| Graneros | 25,961 | 113 | 230.4 | 22,674 | 87.34% | 12,992 | 50.04% | 7,121 | 4,316 | 8,088 | 3,817 | 1,523 | 5.46% | 2,022 | 8.32 | 4,605 | 18.94 | 17,683 | 72.74 | 583.37 | 0 | 0 | 1 | 0 | 4.54% |
| Mostazal | 21,866 | 524 | 41.7 | 17,903 | 81.88% | 11,038 | 50.48% | 5,711 | 3,588 | 6,396 | 3,292 | 1,226 | 5.46% | 1,824 | 9.11 | 4,497 | 22.45 | 13,706 | 68.44 | 572.64 | 0 | 0 | 1 | 0 | 4.54% |
| La Estrella | 4,221 | 435 | 9.7 | 1,380 | 32.69% | 2,766 | 65.53% | 648 | 374 | 917 | 617 | 308 | 5.46% | 223 | 5.28 | 755 | 17.89 | 3,243 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Pichilemu | 12,392 | 749 | 16.5 | 9,459 | 76.33% | 6,440 | 51.97% | 3,383 | 1,755 | 3,864 | 2,077 | 1,006 | 5.46% | 988 | 8.64 | 3,218 | 28.14 | 7,229 | 63.22 | 517.63 | 0 | 0 | 1 | 0 | 4.54% |
| Marchihue | 6,904 | 660 | 10.5 | 2,208 | 31.98% | 3,549 | 51.40% | 1,583 | 963 | 2,033 | 1,262 | 646 | 5.46% | 365 | 5.28 | 1,235 | 17.89 | 5,304 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Paredones | 6,695 | 562 | 11.9 | 2,195 | 32.79% | 3,562 | 53.20% | 1,783 | 938 | 1,836 | 1,244 | 726 | 5.46% | 353 | 5.28 | 1,198 | 17.89 | 5,144 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Pichidegua | 17,756 | 320 | 55.5 | 4,965 | 27.96% | 9,208 | 51.86% | 4,632 | 2,858 | 5,377 | 3,067 | 1,416 | 5.46% | 937 | 5.28 | 3,177 | 17.89 | 13,642 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Peumo | 13,948 | 153 | 91.1 | 7,628 | 54.69% | 7,128 | 51.10% | 3,848 | 2,160 | 4,081 | 2,334 | 1,048 | 5.46% | 736 | 5.28 | 2,495 | 17.89 | 10,716 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| San Vicente | 40,253 | 476 | 84.6 | 21,965 | 54.57% | 20,095 | 49.92% | 10,082 | 5,885 | 11,310 | 6,982 | 3,268 | 5.46% | 1,529 | 4.14 | 6,204 | 16.80 | 29,204 | 79.06 | 715.50 | 0 | 0 | 1 | 0 | 4.54% |
| Coinco | 6,385 | 98 | 65.0 | 4,102 | 64.24% | 3,293 | 51.57% | 1,585 | 1,011 | 1,688 | 1,082 | 633 | 5.46% | 337 | 5.28 | 1,142 | 17.89 | 4,906 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Quinta de Tilcoco | 11,380 | 93 | 122.1 | 5,850 | 51.41% | 5,811 | 51.06% | 3,874 | 2,167 | 3,774 | 1,963 | 778 | 5.46% | 601 | 5.28 | 2,036 | 17.89 | 8,743 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Olivar | 12,335 | 45 | 276.6 | 7,898 | 64.03% | 6,244 | 50.62% | 4,204 | 2,834 | 4,728 | 2,024 | 712 | 5.46% | 651 | 5.28 | 2,207 | 17.89 | 9,477 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Requinoa | 22,161 | 673 | 32.9 | 11,167 | 50.39% | 11,378 | 51.34% | 6,928 | 4,133 | 7,953 | 3,417 | 1,164 | 5.46% | 0 | 0.00 | 4,702 | 20.63 | 18,087 | 79.37 | 535.07 | 0 | 0 | 1 | 0 | 4.54% |
| Rengo | 50,830 | 592 | 85.9 | 37,075 | 72.94% | 25,311 | 49.80% | 15,739 | 8,839 | 16,323 | 8,210 | 3,092 | 5.46% | 4,160 | 8.25 | 8,746 | 17.33 | 37,548 | 74.42 | 698.26 | 0 | 0 | 1 | 0 | 4.54% |
| Malloa | 12,872 | 113 | 114.3 | 4,709 | 36.58% | 6,666 | 51.79% | 3,856 | 2,239 | 3,861 | 2,227 | 991 | 5.46% | 680 | 5.28 | 2,303 | 17.89 | 9,890 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Codegua | 10,796 | 287 | 37.6 | 5,253 | 48.66% | 5,551 | 51.42% | 3,026 | 2,013 | 3,438 | 1,592 | 621 | 5.46% | 570 | 5.28 | 1,931 | 17.89 | 8,295 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Machali | 28,628 | 2,586 | 11.1 | 26,852 | 93.80% | 14,297 | 49.94% | 7,319 | 4,546 | 9,493 | 4,568 | 1,544 | 5.46% | 0 | 0.00 | 5,083 | 20.24 | 20,025 | 79.76 | 1,481.83 | 0 | 0 | 1 | 0 | 4.54% |
| Peralillo | 9,729 | 283 | 34.4 | 5,882 | 60.46% | 5,007 | 51.46% | 2,778 | 1,530 | 2,744 | 1,816 | 904 | 5.46% | 514 | 5.28 | 1,741 | 17.89 | 7,475 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Pumanque | 3,442 | 441 | 7.8 | 0 | 0.00% | 1,793 | 52.09% | 972 | 513 | 1,038 | 687 | 439 | 5.46% | 182 | 5.28 | 616 | 17.89 | 2,644 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Lolol | 6,191 | 597 | 10.4 | 2,118 | 34.21% | 3,235 | 52.25% | 1,397 | 798 | 1,514 | 1,096 | 633 | 5.46% | 327 | 5.28 | 1,108 | 17.89 | 4,757 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Palmilla | 11,200 | 237 | 47.2 | 2,088 | 18.64% | 5,825 | 52.01% | 3,364 | 1,808 | 3,573 | 1,975 | 898 | 5.46% | 591 | 5.28 | 2,004 | 17.89 | 8,605 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Santa Cruz | 32,387 | 420 | 77.2 | 18,603 | 57.44% | 16,160 | 49.90% | 8,728 | 4,964 | 9,112 | 5,479 | 2,620 | 5.46% | 2,116 | 7.11 | 6,120 | 20.55 | 21,545 | 72.34 | 486.30 | 0 | 0 | 1 | 0 | 4.54% |
| Chépica | 13,857 | 503 | 27.5 | 6,949 | 50.15% | 7,100 | 51.24% | 4,290 | 2,391 | 4,245 | 2,468 | 1,284 | 5.46% | 1,697 | 11.73 | 3,839 | 26.53 | 8,936 | 61.75 | 444.92 | 0 | 0 | 1 | 0 | 4.54% |
| Nancagua | 15,634 | 111 | 140.5 | 9,264 | 59.26% | 7,959 | 50.91% | 4,827 | 2,550 | 4,740 | 2,597 | 1,257 | 5.46% | 0 | 0.00 | 4,320 | 27.74 | 11,252 | 72.26 | 501.80 | 0 | 0 | 1 | 0 | 4.54% |
| Placilla | 8,078 | 147 | 55.0 | 2,114 | 26.17% | 4,134 | 51.18% | 2,406 | 1,385 | 2,625 | 1,276 | 611 | 5.46% | 427 | 5.28 | 1,445 | 17.89 | 6,206 | 76.83 | 686.27 | 0 | 0 | 1 | 0 | 4.54% |
| Chimbarongo | 32,316 | 498 | 64.9 | 16,889 | 52.26% | 16,612 | 51.40% | 9,423 | 5,668 | 10,430 | 5,455 | 2,334 | 5.46% | 630 | 1.93 | 8,133 | 24.89 | 23,919 | 73.19 | 506.41 | 0 | 0 | 1 | 0 | 4.54% |
| San Fernando | 63,732 | 2,441 | 26.1 | 51,136 | 80.24% | 31,157 | 48.89% | 18,660 | 11,374 | 18,922 | 10,119 | 4,344 | 5.46% | 3,290 | 5.41 | 8,892 | 14.62 | 48,629 | 79.97 | 927.71 | 0 | 0 | 1 | 0 | 4.54% |
| Vichuquén | 4,916 | 426 | 11.5 | 1,368 | 27.83% | 2,596 | 52.81% | 1,473 | 807 | 1,768 | 1,018 | 423 | 4.17% | 286 | 5.82 | 1,094 | 22.26 | 3,536 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Licantén | 6,902 | 273 | 25.3 | 3,974 | 57.58% | 3,654 | 52.94% | 1,963 | 995 | 2,275 | 1,336 | 568 | 4.17% | 402 | 5.82 | 1,536 | 22.26 | 4,964 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Hualañé | 9,741 | 629 | 15.5 | 5,198 | 53.36% | 5,059 | 51.94% | 2,604 | 1,385 | 3,202 | 1,986 | 954 | 4.17% | 567 | 5.82 | 2,168 | 22.26 | 7,006 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Rauco | 8,566 | 309 | 27.8 | 3,114 | 36.35% | 4,364 | 50.95% | 2,416 | 1,250 | 2,522 | 1,569 | 660 | 4.17% | 1,020 | 5.82 | 3,899 | 22.26 | 12,600 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Sagrada Familia | 17,519 | 549 | 31.9 | 5,080 | 29.00% | 9,108 | 51.99% | 4,724 | 2,779 | 5,123 | 2,874 | 1,173 | 4.17% | 1,020 | 5.82 | 3,899 | 22.26 | 12,600 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Teno | 25,596 | 618 | 41.4 | 6,729 | 26.29% | 13,298 | 51.95% | 7,641 | 4,216 | 8,810 | 4,557 | 1,748 | 4.17% | 991 | 3.83 | 3,954 | 15.28 | 20,927 | 80.89 | 615.42 | 0 | 0 | 1 | 0 | 4.04% |
| Curicó | 119,585 | 1,328 | 90.0 | 100,506 | 84.05% | 58,768 | 49.14% | 33,976 | 19,300 | 37,077 | 19,599 | 7,492 | 4.17% | 3,109 | 2.74 | 16,581 | 14.61 | 93,772 | 82.65 | 899.42 | 0 | 0 | 1 | 0 | 4.04% |
| Molina | 38,521 | 1,552 | 24.8 | 28,232 | 73.29% | 19,392 | 50.34% | 10,104 | 6,426 | 11,557 | 6,662 | 2,753 | 4.17% | 2,307 | 6.31 | 10,351 | 28.30 | 23,918 | 65.39 | 547.80 | 0 | 0 | 1 | 0 | 4.04% |
| Romeral | 12,707 | 1,597 | 8.0 | 3,675 | 28.92% | 6,596 | 51.91% | 3,777 | 2,142 | 3,793 | 1,974 | 691 | 4.17% | 740 | 5.82 | 2,828 | 22.26 | 9,139 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Curepto | 10,812 | 1,074 | 10.1 | 3,157 | 29.20% | 5,784 | 53.50% | 3,116 | 1,804 | 3,411 | 2,363 | 1,285 | 4.17% | 629 | 5.82 | 2,406 | 22.26 | 7,776 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Constitución | 46,081 | 1,344 | 34.3 | 37,202 | 80.73% | 23,389 | 50.76% | 15,173 | 7,959 | 14,770 | 6,791 | 2,378 | 4.17% | 9,004 | 19.77 | 13,711 | 30.11 | 22,823 | 50.12 | 617.26 | 0 | 0 | 1 | 0 | 4.04% |
| Empedrado | 4,225 | 565 | 7.5 | 2,499 | 59.15% | 2,222 | 52.59% | 1,522 | 815 | 1,363 | 720 | 320 | 4.17% | 246 | 5.82 | 940 | 22.26 | 3,039 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Pencahue | 8,315 | 957 | 8.7 | 2,037 | 24.50% | 4,517 | 54.32% | 2,022 | 1,161 | 2,485 | 1,527 | 795 | 4.17% | 484 | 5.82 | 1,851 | 22.26 | 5,981 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| San Rafael | 7,674 | 264 | 29.1 | 3,482 | 45.37% | 3,903 | 50.86% | 2,234 | 1,255 | 2,326 | 1,312 | 548 | 4.17% | 447 | 5.82 | 1,708 | 22.26 | 5,519 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Talca | 201,797 | 232 | 871.7 | 193,755 | 96.01% | 96,810 | 47.97% | 53,674 | 32,865 | 57,745 | 33,213 | 12,584 | 4.17% | 4,085 | 2.22 | 33,553 | 18.27 | 145,987 | 79.50 | 947.90 | 0 | 0 | 1 | 0 | 4.04% |
| Maule | 16,837 | 238 | 70.7 | 6,739 | 40.02% | 8,691 | 51.62% | 4,888 | 2,392 | 4,572 | 2,512 | 1,088 | 4.17% | 980 | 5.82 | 3,747 | 22.26 | 12,110 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Rio Claro | 12,698 | 431 | 29.5 | 2,651 | 20.88% | 6,716 | 52.89% | 3,926 | 2,229 | 4,433 | 2,408 | 922 | 4.17% | 739 | 5.82 | 2,826 | 22.26 | 9,133 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Pelarco | 7,266 | 332 | 21.9 | 1,822 | 25.08% | 3,714 | 51.11% | 4,740 | 2,267 | 4,568 | 2,457 | 1,076 | 4.17% | 423 | 5.82 | 1,617 | 22.26 | 5,226 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |

# Table A2.1: Data per Commune



| | | | | | | | | AGE GROUPS (5) | | | | | | | | | | | | | ECONOMIC ACTIVITY (9) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | POP (1) | AREA (2) | DEN | URB (3) | %URB | MEN (4) | %MEN | 0-14 | 15-24 | 25-44 | 45-64 | 65+ | NAT (6) | IND (7) | %IND | PNI (7) | %PNI | NP (7) | %NP | INC (8) | Tra | Min | Agr-Sil | Man | GDP (10) |
| San Clemente | 37,261 | 4,504 | 8.3 | 13,398 | 35.96% | 18,988 | 50.96% | 11,048 | 5,889 | 11,478 | 6,418 | 2,557 | 4.17% | 3,752 | 10.17 | 10,300 | 27.92 | 22,833 | 61.90 | 468.15 | 0 | 0 | 1 | 0 | 4.04% |
| Chanco | 9,457 | 530 | 17.9 | 4,012 | 42.42% | 4,856 | 51.35% | 3,147 | 1,705 | 2,944 | 1,721 | 874 | 4.17% | 550 | 5.82 | 2,105 | 22.26 | 6,802 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Pelluhue | 6,414 | 371 | 17.3 | 3,877 | 60.45% | 3,408 | 53.13% | 1,752 | 820 | 1,530 | 1,031 | 551 | 4.17% | 373 | 5.82 | 1,427 | 22.26 | 4,613 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Cauquenes | 41,217 | 2,126 | 19.4 | 30,771 | 74.66% | 20,092 | 48.75% | 11,827 | 6,486 | 11,574 | 7,654 | 4,265 | 4.17% | 2,546 | 6.28 | 12,088 | 29.82 | 25,902 | 63.90 | 533.73 | 0 | 0 | 1 | 0 | 4.04% |
| San Javier | 37,793 | 1,313 | 28.8 | 22,004 | 58.22% | 18,827 | 49.82% | 10,188 | 5,602 | 11,228 | 6,903 | 3,220 | 4.17% | 2,569 | 7.01 | 10,200 | 27.84 | 23,870 | 65.15 | 559.65 | 0 | 0 | 1 | 0 | 4.04% |
| Retiro | 18,487 | 827 | 22.4 | 4,708 | 25.47% | 9,451 | 51.12% | 6,102 | 3,233 | 6,242 | 3,183 | 1,365 | 4.17% | 1,076 | 5.82 | 4,114 | 22.26 | 13,297 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Parral | 37,822 | 1,638 | 23.1 | 26,397 | 69.79% | 18,963 | 50.14% | 12,029 | 6,242 | 11,975 | 7,025 | 3,095 | 4.17% | 3,283 | 8.34 | 11,493 | 29.18 | 24,609 | 62.48 | 536.39 | 0 | 0 | 1 | 0 | 4.04% |
| Villa Alegre | 14,725 | 190 | 77.6 | 5,456 | 37.05% | 7,332 | 49.79% | 3,991 | 2,340 | 4,270 | 2,899 | 1,295 | 4.17% | 857 | 5.82 | 3,277 | 22.26 | 10,591 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Linares | 83,249 | 1,466 | 56.8 | 68,224 | 81.95% | 40,518 | 48.67% | 25,915 | 14,489 | 25,260 | 14,149 | 6,238 | 4.17% | 5,710 | 6.85 | 20,609 | 24.74 | 56,989 | 68.41 | 650.29 | 0 | 0 | 1 | 0 | 4.04% |
| Longaví | 28,161 | 1,454 | 19.4 | 6,206 | 22.04% | 14,649 | 52.02% | 9,858 | 5,028 | 9,132 | 4,864 | 1,989 | 4.17% | 1,639 | 5.82 | 6,267 | 22.26 | 20,255 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Yerbas Buenas | 16,134 | 262 | 61.6 | 1,595 | 9.89% | 8,380 | 51.94% | 5,081 | 2,795 | 4,796 | 2,672 | 1,000 | 4.17% | 939 | 5.82 | 3,591 | 22.26 | 11,604 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Colbún | 17,619 | 2,900 | 6.1 | 5,152 | 29.24% | 8,943 | 50.76% | 5,354 | 2,901 | 4,929 | 2,910 | 1,343 | 4.17% | 1,025 | 5.82 | 3,921 | 22.26 | 12,672 | 71.92 | 637.60 | 0 | 0 | 1 | 0 | 4.04% |
| Cobquecura | 5,687 | 570 | 10.0 | 1,493 | 26.25% | 3,032 | 53.31% | 1,721 | 929 | 1,819 | 1,344 | 742 | 7.55% | 439 | 7.71 | 1,245 | 21.89 | 4,004 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Quirihue | 11,429 | 589 | 19.4 | 7,952 | 69.58% | 5,852 | 51.20% | 3,194 | 1,675 | 3,306 | 2,106 | 978 | 7.55% | 881 | 7.71 | 2,502 | 21.89 | 8,046 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Ninhue | 5,738 | 401 | 14.3 | 1,433 | 24.97% | 2,920 | 50.89% | 1,745 | 938 | 1,759 | 1,164 | 564 | 7.55% | 443 | 7.71 | 1,256 | 21.89 | 4,039 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| San Carlos | 50,088 | 874 | 57.3 | 31,018 | 61.93% | 24,910 | 49.73% | 15,659 | 7,935 | 15,398 | 8,946 | 3,918 | 7.55% | 3,539 | 6.86 | 8,891 | 17.24 | 39,141 | 75.90 | 630.63 | 0 | 0 | 0 | 1 | 8.44% |
| Ñiquén | 11,421 | 493 | 23.2 | 1,143 | 10.01% | 5,886 | 51.54% | 3,638 | 2,035 | 4,049 | 2,610 | 1,268 | 7.55% | 881 | 7.71 | 2,500 | 21.89 | 8,040 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| San Fabián | 3,646 | 1,568 | 2.3 | 1,452 | 39.82% | 1,877 | 51.48% | 1,219 | 456 | 961 | 690 | 336 | 7.55% | 281 | 7.71 | 798 | 21.89 | 2,567 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Trehuaco | 5,296 | 313 | 16.9 | 1,245 | 23.51% | 2,788 | 52.64% | 1,456 | 815 | 1,669 | 993 | 472 | 7.55% | 408 | 7.71 | 1,159 | 21.89 | 3,728 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Coelemu | 16,082 | 342 | 47.0 | 9,845 | 61.22% | 8,086 | 50.28% | 5,039 | 2,593 | 5,160 | 2,960 | 1,416 | 7.55% | 1,240 | 7.71 | 3,520 | 21.89 | 11,321 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Portezuelo | 5,470 | 282 | 19.4 | 1,750 | 31.99% | 2,825 | 51.65% | 1,410 | 805 | 1,452 | 1,039 | 488 | 7.55% | 422 | 7.71 | 1,197 | 21.89 | 3,851 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Ránquil | 5,683 | 248 | 22.9 | 1,337 | 23.53% | 2,896 | 50.96% | 1,474 | 833 | 1,619 | 1,212 | 626 | 7.55% | 438 | 7.71 | 1,244 | 21.89 | 4,001 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| San Nicolás | 9,741 | 491 | 19.9 | 3,428 | 35.19% | 5,032 | 51.66% | 2,606 | 1,443 | 3,030 | 1,902 | 806 | 7.55% | 751 | 7.71 | 2,132 | 21.89 | 6,857 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Chillán | 161,953 | 511 | 316.8 | 148,015 | 91.39% | 77,007 | 47.55% | 55,001 | 33,726 | 55,717 | 32,728 | 13,320 | 7.55% | 11,133 | 6.62 | 24,823 | 14.77 | 132,106 | 78.61 | 775.75 | 0 | 0 | 0 | 1 | 8.44% |
| Chillán Viejo | 22,084 | 292 | 75.7 | 18,827 | 85.25% | 10,791 | 48.86% | 6,959 | 3,978 | 7,179 | 3,953 | 1,578 | 7.55% | 1,716 | 8.80 | 4,274 | 21.91 | 13,517 | 69.29 | 561.66 | 0 | 0 | 0 | 1 | 8.44% |
| Bulnes | 20,595 | 425 | 48.4 | 12,514 | 60.76% | 10,275 | 49.89% | 6,235 | 3,433 | 6,060 | 3,264 | 1,498 | 7.55% | 1,588 | 7.71 | 4,508 | 21.89 | 14,498 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Quillón | 15,146 | 423 | 35.8 | 7,536 | 49.76% | 7,699 | 50.83% | 3,997 | 2,148 | 3,979 | 2,672 | 1,297 | 7.55% | 1,168 | 7.71 | 3,315 | 21.89 | 10,662 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Pemuco | 8,821 | 563 | 15.7 | 3,844 | 43.58% | 4,578 | 51.90% | 2,733 | 1,464 | 2,678 | 1,459 | 727 | 7.55% | 680 | 7.71 | 1,931 | 21.89 | 6,210 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Coihueco | 23,583 | 1,777 | 13.3 | 7,230 | 30.66% | 12,211 | 51.78% | 7,692 | 3,885 | 7,134 | 3,798 | 1,599 | 7.55% | 4,988 | 20.72 | 6,678 | 27.75 | 12,403 | 51.53 | 587.15 | 0 | 0 | 0 | 1 | 8.44% |
| Pinto | 9,875 | 1,164 | 8.5 | 4,278 | 43.32% | 5,035 | 50.99% | 2,599 | 1,303 | 2,484 | 1,483 | 741 | 7.55% | 762 | 7.71 | 2,162 | 21.89 | 6,952 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| San Ignacio | 16,106 | 364 | 44.3 | 4,873 | 30.26% | 8,192 | 50.86% | 5,468 | 2,786 | 5,186 | 3,006 | 1,476 | 7.55% | 1,242 | 7.71 | 3,526 | 21.89 | 11,338 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| El Carmen | 12,845 | 664 | 19.3 | 4,426 | 34.46% | 6,567 | 51.12% | 4,513 | 2,476 | 4,336 | 2,536 | 1,184 | 7.55% | 991 | 7.71 | 2,812 | 21.89 | 9,043 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Yungay | 16,814 | 824 | 20.4 | 11,469 | 68.21% | 8,565 | 50.94% | 4,796 | 2,133 | 4,829 | 2,834 | 1,354 | 7.55% | 1,297 | 7.71 | 3,680 | 21.89 | 11,837 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Tomé | 52,440 | 495 | 106.0 | 45,959 | 87.64% | 25,263 | 48.18% | 14,702 | 8,195 | 14,871 | 9,191 | 4,131 | 7.55% | 6,009 | 11.98 | 13,940 | 27.79 | 30,207 | 60.23 | 514.08 | 0 | 0 | 0 | 1 | 8.44% |
| Florida | 10,177 | 609 | 16.7 | 3,875 | 38.08% | 5,231 | 51.40% | 2,838 | 1,488 | 2,937 | 1,903 | 910 | 7.55% | 785 | 7.71 | 2,228 | 21.89 | 7,164 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Penco | 46,016 | 108 | 427.7 | 45,361 | 98.58% | 22,366 | 48.60% | 13,076 | 7,758 | 14,655 | 7,924 | 2,520 | 7.55% | 0 | 0.00 | 18,464 | 41.01 | 26,564 | 58.99 | 545.32 | 0 | 0 | 0 | 1 | 8.44% |
| Concepción | 216,061 | 222 | 975.0 | 212,003 | 98.12% | 103,860 | 48.07% | 103,887 | 67,312 | 118,456 | 64,237 | 24,027 | 7.55% | 0 | 0.00 | 30,077 | 14.39 | 178,966 | 85.61 | 1,448.46 | 0 | 0 | 0 | 1 | 8.44% |
| Talcahuano | 250,348 | 146 | 1,717.1 | 248,964 | 99.45% | 121,778 | 48.64% | 82,599 | 49,118 | 88,054 | 45,443 | 16,433 | 7.55% | 20,153 | 7.39 | 48,293 | 17.72 | 204,148 | 74.89 | 772.00 | 0 | 0 | 0 | 1 | 8.44% |
| San Pedro de la Paz | 80,447 | 113 | 715.1 | 80,159 | 99.64% | 38,571 | 47.95% | 25,351 | 14,489 | 26,152 | 14,399 | 5,749 | 7.55% | 5,065 | 5.64 | 26,360 | 29.34 | 58,433 | 65.03 | 1,413.64 | 0 | 0 | 0 | 1 | 8.44% |
| Chiguayante | 81,302 | 72 | 1,137.1 | 81,238 | 99.92% | 38,524 | 47.38% | 25,621 | 14,643 | 26,430 | 14,552 | 5,811 | 7.55% | 3,270 | 5.38 | 11,289 | 18.57 | 46,239 | 76.05 | 1,014.12 | 0 | 0 | 0 | 1 | 8.44% |
| Coronel | 95,528 | 279 | 341.9 | 91,469 | 95.75% | 46,766 | 48.96% | 29,065 | 15,134 | 30,001 | 14,742 | 5,362 | 7.55% | 12,003 | 12.92 | 29,304 | 31.53 | 51,621 | 55.55 | 499.98 | 0 | 0 | 0 | 1 | 8.44% |
| Hualqui | 18,768 | 531 | 35.4 | 14,756 | 78.62% | 9,293 | 49.52% | 5,113 | 2,903 | 4,829 | 2,866 | 1,299 | 7.55% | 1,448 | 7.71 | 4,108 | 21.89 | 13,212 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Lota | 49,089 | 136 | 361.5 | 48,975 | 99.77% | 23,944 | 48.78% | 15,555 | 8,645 | 15,900 | 8,588 | 3,191 | 7.55% | 6,333 | 12.33 | 15,698 | 30.57 | 29,312 | 57.09 | 504.95 | 0 | 0 | 0 | 1 | 8.44% |
| Santa Juana | 12,713 | 731 | 17.4 | 7,095 | 55.81% | 6,357 | 50.00% | 3,798 | 1,777 | 3,478 | 2,127 | 1,084 | 7.55% | 981 | 7.71 | 2,783 | 21.89 | 8,950 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Yumbel | 20,498 | 727 | 28.2 | 10,935 | 53.35% | 10,442 | 50.94% | 5,615 | 3,039 | 5,513 | 3,874 | 1,936 | 7.55% | 1,581 | 7.71 | 4,487 | 21.89 | 14,430 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Cabrero | 25,282 | 640 | 39.5 | 18,037 | 71.34% | 12,888 | 50.98% | 7,145 | 3,796 | 7,731 | 3,840 | 1,555 | 7.55% | 1,950 | 7.71 | 5,534 | 21.89 | 17,798 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| San Rosendo | 3,918 | 92 | 42.4 | 3,249 | 82.92% | 1,930 | 49.26% | 1,249 | 659 | 1,251 | 824 | 313 | 7.55% | 302 | 7.71 | 858 | 21.89 | 2,758 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Laja | 22,404 | 340 | 65.9 | 16,288 | 72.70% | 11,113 | 49.60% | 7,546 | 4,097 | 7,967 | 4,542 | 1,532 | 7.55% | 2,886 | 11.42 | 5,795 | 22.93 | 16,589 | 65.65 | 548.11 | 0 | 0 | 0 | 1 | 8.44% |
| Nacimiento | 25,971 | 935 | 27.8 | 20,884 | 80.41% | 13,090 | 50.40% | 9,313 | 4,661 | 9,004 | 4,515 | 1,665 | 7.55% | 4,904 | 17.03 | 7,758 | 26.95 | 16,129 | 56.02 | 459.69 | 0 | 0 | 0 | 1 | 8.44% |
| Los Angeles | 166,556 | 1,748 | 95.3 | 123,445 | 74.12% | 81,863 | 49.15% | 49,384 | 26,706 | 49,252 | 25,431 | 9,839 | 7.55% | 7,710 | 4.92 | 29,377 | 18.75 | 119,623 | 76.33 | 1,012.13 | 0 | 0 | 0 | 1 | 8.44% |
| Quilleco | 10,428 | 1,122 | 9.3 | 5,486 | 52.61% | 5,378 | 51.57% | 2,772 | 1,343 | 2,641 | 2,040 | 1,090 | 7.55% | 804 | 7.71 | 2,283 | 21.89 | 7,341 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Tucapel | 12,777 | 915 | 14.0 | 8,827 | 69.09% | 6,403 | 50.11% | 3,745 | 2,055 | 3,764 | 2,382 | 1,240 | 7.55% | 985 | 7.71 | 2,797 | 21.89 | 8,995 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Antuco | 3,908 | 1,884 | 2.1 | 1,978 | 50.61% | 1,981 | 50.69% | 854 | 534 | 871 | 632 | 371 | 7.55% | 301 | 7.71 | 855 | 21.89 | 2,751 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Santa Bárbara | 19,970 | 3,380 | 5.9 | 7,932 | 39.72% | 10,835 | 54.26% | 6,131 | 3,197 | 5,394 | 3,092 | 1,330 | 7.55% | 1,540 | 7.71 | 4,371 | 21.89 | 14,058 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Quilaco | 4,021 | 1,124 | 3.6 | 1,612 | 40.09% | 2,110 | 52.47% | 1,124 | 580 | 1,141 | 918 | 406 | 7.55% | 310 | 7.71 | 880 | 21.89 | 2,831 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Mulchén | 29,003 | 1,925 | 15.1 | 21,819 | 75.23% | 14,513 | 50.04% | 9,996 | 5,083 | 8,982 | 5,190 | 2,230 | 7.55% | 8,620 | 27.43 | 10,087 | 32.10 | 12,716 | 40.47 | 435.08 | 0 | 0 | 0 | 1 | 8.44% |
| Negrete | 8,579 | 157 | 54.8 | 5,283 | 61.58% | 4,414 | 51.45% | 3,271 | 1,389 | 2,942 | 1,519 | 629 | 7.55% | 662 | 7.71 | 1,878 | 21.89 | 6,039 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Arauco | 34,873 | 956 | 36.5 | 24,269 | 69.59% | 17,603 | 50.48% | 10,721 | 5,917 | 10,240 | 4,985 | 1,965 | 7.55% | 4,015 | 12.01 | 8,892 | 26.60 | 20,523 | 61.39 | 585.28 | 0 | 0 | 0 | 1 | 8.44% |
| Curanilahue | 31,943 | 994 | 32.1 | 30,126 | 94.31% | 16,115 | 50.45% | 11,782 | 6,706 | 12,155 | 5,855 | 1,932 | 7.55% | 5,555 | 14.70 | 12,531 | 33.15 | 19,715 | 52.15 | 421.49 | 0 | 0 | 0 | 1 | 8.44% |
| Lebu | 25,035 | 561 | 44.6 | 21,991 | 87.84% | 12,416 | 49.59% | 8,317 | 4,620 | 7,897 | 4,098 | 1,542 | 7.55% | 3,172 | 12.41 | 8,181 | 32.02 | 14,198 | 55.57 | 456.87 | 0 | 0 | 0 | 1 | 8.44% |
| Los Alamos | 18,632 | 599 | 31.1 | 16,394 | 87.99% | 9,456 | 50.75% | 6,233 | 3,278 | 5,505 | 2,807 | 1,232 | 7.55% | 1,437 | 7.71 | 4,078 | 21.89 | 13,117 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Cañete | 31,270 | 760 | 41.1 | 19,839 | 63.44% | 15,625 | 49.97% | 10,300 | 5,580 | 9,119 | 5,452 | 2,163 | 7.55% | 5,068 | 15.90 | 8,901 | 27.93 | 17,904 | 56.17 | 586.58 | 0 | 0 | 0 | 1 | 8.44% |
| Contulmo | 5,838 | 962 | 6.1 | 2,442 | 41.83% | 3,020 | 51.73% | 1,805 | 967 | 1,792 | 1,099 | 573 | 7.55% | 450 | 7.71 | 1,278 | 21.89 | 4,110 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Tirúa | 9,664 | 624 | 15.5 | 2,508 | 25.95% | 5,028 | 52.03% | 3,705 | 1,906 | 2,671 | 1,381 | 563 | 7.55% | 745 | 7.71 | 2,115 | 21.89 | 6,803 | 70.40 | 688.65 | 0 | 0 | 0 | 1 | 8.44% |
| Angol | 48,996 | 1,194 | 41.0 | 43,801 | 89.40% | 23,770 | 48.51% | 16,138 | 9,698 | 15,308 | 8,266 | 3,801 | 18.61% | 8,288 | 16.70 | 18,174 | 36.61 | 23,175 | 46.69 | 482.52 | 0 | 0 | 1 | 0 | 2.40% |
| Renaico | 9,128 | 267 | 34.1 | 6,878 | 75.35% | 4,508 | 49.39% | 3,025 | 1,638 | 2,781 | 1,572 | 726 | 18.61% | 974 | 10.67 | 1,910 | 20.92 | 6,244 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |

# Table A2.1: Data per Commune



| | | | | | | | | AGE GROUPS (5) | | | | | | | | | | | | | ECONOMIC ACTIVITY (9) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | POP (1) | AREA (2) | DEN | URB (3) | %URB | MEN (4) | %MEN | 0-14 | 15-24 | 25-44 | 45-64 | 65+ | NAT (6) | IND (7) | %IND | PNI (7) | %PNI | NP (7) | %NP | INC (8) | Tra | Min | Agr-Sil | Man | GDP (10) |
| Collipulli | 22,354 | 1,296 | 17.2 | 16,006 | 71.60% | 11,106 | 49.68% | 8,106 | 4,505 | 7,893 | 3,897 | 1,799 | 18.61% | 3,636 | 14.54 | 7,394 | 29.57 | 13,971 | 55.88 | 458.74 | 0 | 0 | 1 | 0 | 2.40% |
| Lonquimay | 10,237 | 3,914 | 2.6 | 3,435 | 33.55% | 5,414 | 52.89% | 2,638 | 1,651 | 2,377 | 1,370 | 696 | 18.61% | 1,092 | 10.67 | 2,142 | 20.92 | 7,002 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Purén | 12,868 | 465 | 27.7 | 7,604 | 59.09% | 6,408 | 49.80% | 4,956 | 2,636 | 4,335 | 2,370 | 1,138 | 18.61% | 1,373 | 10.67 | 2,693 | 20.92 | 8,802 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Los Sauces | 7,581 | 850 | 8.9 | 3,638 | 47.99% | 3,847 | 50.75% | 2,503 | 1,497 | 2,471 | 1,432 | 784 | 18.61% | 809 | 10.67 | 1,586 | 20.92 | 5,186 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Ercilla | 9,041 | 500 | 18.1 | 3,238 | 35.81% | 4,633 | 51.24% | 2,710 | 1,500 | 2,179 | 1,444 | 753 | 18.61% | 965 | 10.67 | 1,892 | 20.92 | 6,184 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Lumaco | 11,405 | 1,119 | 10.2 | 4,132 | 36.23% | 6,074 | 53.26% | 3,991 | 2,050 | 3,692 | 2,106 | 869 | 18.61% | 1,217 | 10.67 | 2,386 | 20.92 | 7,801 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Traiguén | 19,534 | 908 | 21.5 | 14,140 | 72.39% | 9,734 | 49.83% | 5,933 | 3,745 | 6,010 | 3,634 | 1,850 | 18.61% | 3,403 | 17.23 | 5,566 | 28.18 | 10,781 | 54.59 | 498.66 | 0 | 0 | 1 | 0 | 2.40% |
| Victoria | 33,501 | 1,256 | 26.7 | 23,977 | 71.57% | 16,423 | 49.02% | 10,539 | 5,873 | 9,777 | 5,861 | 2,680 | 18.61% | 5,039 | 15.29 | 9,001 | 27.32 | 18,909 | 57.39 | 469.69 | 0 | 0 | 1 | 0 | 2.40% |
| Curacautín | 16,970 | 1,664 | 10.2 | 12,412 | 73.14% | 8,310 | 48.97% | 5,011 | 3,033 | 4,806 | 3,091 | 1,641 | 18.61% | 1,811 | 10.67 | 3,551 | 20.92 | 11,608 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Carahue | 25,696 | 1,341 | 19.2 | 11,596 | 45.13% | 13,017 | 50.66% | 8,502 | 4,177 | 7,357 | 4,496 | 2,118 | 18.61% | 4,444 | 17.07 | 8,773 | 33.70 | 12,812 | 49.22 | 406.19 | 0 | 0 | 1 | 0 | 2.40% |
| Nueva Imperial | 40,059 | 1,160 | 34.5 | 18,335 | 45.77% | 20,423 | 50.98% | 12,809 | 6,831 | 10,682 | 6,449 | 3,509 | 18.61% | 5,217 | 13.91 | 12,164 | 32.44 | 20,115 | 53.65 | 345.89 | 0 | 0 | 1 | 0 | 2.40% |
| Galvarino | 12,596 | 568 | 22.2 | 3,539 | 28.10% | 6,500 | 51.60% | 4,902 | 2,421 | 4,044 | 2,333 | 1,140 | 18.61% | 1,344 | 10.67 | 2,636 | 20.92 | 8,616 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Perquenco | 6,450 | 331 | 19.5 | 2,929 | 45.41% | 3,281 | 50.87% | 1,656 | 906 | 1,619 | 1,002 | 500 | 18.61% | 688 | 10.67 | 1,350 | 20.92 | 4,412 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Lautaro | 32,218 | 901 | 35.8 | 21,071 | 65.40% | 15,991 | 49.63% | 8,802 | 5,404 | 8,115 | 4,824 | 2,357 | 18.61% | 3,092 | 10.89 | 6,546 | 23.06 | 18,744 | 66.04 | 831.55 | 0 | 0 | 1 | 0 | 2.40% |
| Vilcún | 22,491 | 1,421 | 15.8 | 9,024 | 40.12% | 11,392 | 50.65% | 6,525 | 3,746 | 6,109 | 3,470 | 1,712 | 18.61% | 3,196 | 15.28 | 5,710 | 27.29 | 12,014 | 57.43 | 373.06 | 0 | 0 | 1 | 0 | 2.40% |
| Melipeuco | 5,628 | 1,107 | 5.1 | 2,333 | 41.45% | 2,906 | 51.63% | 1,469 | 858 | 1,369 | 936 | 508 | 18.61% | 601 | 10.67 | 1,178 | 20.92 | 3,850 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Temuco | 245,347 | 464 | 528.8 | 232,528 | 94.78% | 117,071 | 47.72% | 84,562 | 56,682 | 90,947 | 45,549 | 18,548 | 18.61% | 7,495 | 3.29 | 21,407 | 9.39 | 198,961 | 87.32 | 1,352.88 | 0 | 0 | 1 | 0 | 2.40% |
| Padre Las Casas | 58,795 | 401 | 146.7 | 33,697 | 57.31% | 29,327 | 49.88% | 17,547 | 10,366 | 17,004 | 9,437 | 4,441 | 18.61% | 10,388 | 18.35 | 16,167 | 28.55 | 30,065 | 53.10 | 472.23 | 0 | 0 | 1 | 0 | 2.40% |
| Saavedra | 14,034 | 401 | 35.0 | 2,679 | 19.09% | 7,259 | 51.72% | 5,125 | 2,379 | 3,697 | 2,411 | 1,341 | 18.61% | 1,498 | 10.67 | 2,937 | 20.92 | 9,600 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Teodoro Schmidt | 15,504 | 650 | 23.9 | 6,244 | 40.27% | 8,136 | 52.48% | 4,844 | 2,457 | 4,368 | 2,643 | 1,250 | 18.61% | 1,655 | 10.67 | 3,244 | 20.92 | 10,605 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Freire | 25,514 | 935 | 27.3 | 7,629 | 29.90% | 13,143 | 51.51% | 7,112 | 4,103 | 6,894 | 4,299 | 2,072 | 18.61% | 2,226 | 9.34 | 5,663 | 23.77 | 15,939 | 66.89 | 351.27 | 0 | 0 | 1 | 0 | 2.40% |
| Cunco | 18,703 | 1,907 | 9.8 | 8,806 | 47.08% | 9,203 | 49.21% | 5,832 | 3,144 | 5,072 | 3,188 | 1,664 | 18.61% | 1,996 | 10.67 | 3,914 | 20.92 | 12,794 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Toltén | 11,216 | 860 | 13.0 | 4,123 | 36.76% | 5,827 | 51.95% | 4,326 | 2,045 | 3,815 | 2,021 | 1,147 | 18.61% | 1,197 | 10.67 | 2,347 | 20.92 | 7,672 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Pitrufquén | 21,988 | 581 | 37.9 | 13,420 | 61.03% | 10,902 | 49.58% | 5,534 | 3,043 | 6,022 | 3,727 | 2,221 | 18.61% | 2,637 | 13.28 | 4,230 | 21.31 | 12,987 | 65.41 | 635.75 | 0 | 0 | 1 | 0 | 2.40% |
| Gorbea | 15,222 | 695 | 21.9 | 9,413 | 61.84% | 7,609 | 49.99% | 4,468 | 2,247 | 4,075 | 2,754 | 1,618 | 18.61% | 3,110 | 21.32 | 4,277 | 29.32 | 7,202 | 49.37 | 412.31 | 0 | 0 | 1 | 0 | 2.40% |
| Loncoche | 23,037 | 977 | 23.6 | 15,223 | 66.08% | 11,499 | 49.92% | 7,317 | 3,846 | 7,035 | 4,088 | 2,174 | 18.61% | 3,677 | 15.81 | 5,402 | 23.22 | 14,184 | 60.97 | 559.89 | 0 | 0 | 1 | 0 | 2.40% |
| Villarrica | 45,531 | 1,291 | 35.3 | 30,859 | 67.78% | 22,694 | 49.84% | 11,608 | 6,702 | 11,159 | 6,319 | 3,036 | 18.61% | 2,870 | 7.59 | 4,383 | 11.59 | 30,575 | 80.83 | 717.53 | 0 | 0 | 1 | 0 | 2.40% |
| Pucón | 21,107 | 1,249 | 16.9 | 13,837 | 65.56% | 10,705 | 50.72% | 5,236 | 2,661 | 4,697 | 2,430 | 1,191 | 18.61% | 2,252 | 10.67 | 4,417 | 20.92 | 14,438 | 68.40 | 553.99 | 0 | 0 | 1 | 0 | 2.40% |
| Curarrehue | 6,784 | 1,171 | 5.8 | 1,862 | 27.45% | 3,586 | 52.86% | 1,964 | 1,021 | 1,450 | 859 | 494 | 18.61% | 583 | 10.82 | 1,028 | 19.08 | 3,778 | 70.11 | 495.65 | 0 | 0 | 1 | 0 | 2.40% |
| Mariquina | 18,223 | 1,321 | 13.8 | 8,925 | 48.98% | 9,361 | 51.37% | 5,942 | 3,328 | 5,391 | 3,018 | 1,507 | 7.49% | 1,225 | 6.72 | 3,296 | 18.09 | 13,703 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Lanco | 15,107 | 532 | 28.4 | 10,383 | 68.73% | 7,415 | 49.08% | 4,302 | 2,537 | 4,039 | 2,406 | 1,289 | 7.49% | 1,015 | 6.72 | 2,732 | 18.09 | 11,360 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Panguipulli | 33,273 | 3,292 | 10.1 | 15,888 | 47.75% | 17,059 | 51.27% | 9,055 | 4,624 | 8,701 | 5,230 | 2,522 | 7.49% | 2,236 | 6.72 | 6,017 | 18.09 | 25,020 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Máfil | 7,213 | 583 | 12.4 | 3,796 | 52.63% | 3,773 | 52.31% | 2,375 | 1,037 | 2,052 | 1,347 | 653 | 7.49% | 485 | 6.72 | 1,304 | 18.09 | 5,424 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Valdivia | 140,559 | 1,016 | 138.4 | 129,952 | 92.45% | 68,510 | 48.74% | 36,638 | 24,267 | 41,275 | 22,378 | 9,850 | 7.49% | 12,209 | 9.36 | 24,416 | 18.72 | 93,800 | 71.92 | 807.20 | 0 | 0 | 1 | 0 | 4.25% |
| Los Lagos | 20,168 | 1,791 | 11.3 | 9,479 | 47.00% | 10,370 | 51.42% | 5,692 | 3,147 | 5,729 | 3,270 | 1,391 | 7.49% | 1,355 | 6.72 | 3,647 | 18.09 | 15,165 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Futrono | 14,981 | 2,121 | 7.1 | 8,399 | 56.06% | 7,647 | 51.04% | 5,479 | 2,775 | 4,351 | 2,388 | 920 | 7.49% | 1,007 | 6.72 | 2,709 | 18.09 | 11,265 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Corral | 5,463 | 767 | 7.1 | 3,670 | 67.18% | 2,864 | 52.43% | 1,824 | 935 | 1,934 | 1,039 | 514 | 7.49% | 367 | 6.72 | 988 | 18.09 | 4,108 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Paillaco | 19,237 | 896 | 21.5 | 9,973 | 51.84% | 9,620 | 50.01% | 5,308 | 2,752 | 5,176 | 3,141 | 1,588 | 7.49% | 1,293 | 6.72 | 3,479 | 18.09 | 14,465 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| La Unión | 39,447 | 2,137 | 18.5 | 25,615 | 64.94% | 20,125 | 51.02% | 13,437 | 6,690 | 12,510 | 7,001 | 2,849 | 7.49% | 2,651 | 6.72 | 7,134 | 18.09 | 29,662 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Lago Ranco | 10,098 | 1,763 | 5.7 | 2,205 | 21.84% | 5,295 | 52.44% | 3,869 | 1,782 | 2,926 | 1,839 | 848 | 7.49% | 679 | 6.72 | 1,826 | 18.09 | 7,593 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| RioBueno | 32,627 | 2,212 | 14.8 | 15,054 | 46.14% | 16,418 | 50.32% | 10,461 | 5,250 | 9,898 | 6,249 | 2,708 | 7.49% | 2,193 | 6.72 | 5,901 | 18.09 | 24,534 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| San Juan de la Costa | 8,831 | 1,517 | 5.8 | 902 | 10.21% | 4,814 | 54.51% | 3,372 | 1,819 | 3,182 | 1,974 | 920 | 7.49% | 593 | 6.72 | 1,597 | 18.09 | 6,640 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| San Pablo | 10,162 | 637 | 15.9 | 3,478 | 34.23% | 5,210 | 51.27% | 3,063 | 1,645 | 3,124 | 2,167 | 1,116 | 7.49% | 683 | 6.72 | 1,838 | 18.09 | 7,641 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Osorno | 145,475 | 951 | 152.9 | 132,245 | 90.91% | 70,743 | 48.63% | 39,608 | 25,053 | 43,861 | 23,937 | 10,591 | 7.49% | 11,645 | 8.38 | 26,369 | 18.98 | 100,917 | 72.64 | 704.29 | 0 | 0 | 1 | 0 | 4.25% |
| Puyehue | 11,368 | 1,598 | 7.1 | 3,932 | 34.59% | 6,008 | 52.85% | 3,196 | 1,720 | 3,510 | 1,837 | 908 | 7.49% | 764 | 6.72 | 2,056 | 18.09 | 8,548 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Río Negro | 14,732 | 1,266 | 11.6 | 6,583 | 44.69% | 7,528 | 51.10% | 4,443 | 2,566 | 4,294 | 2,926 | 1,346 | 7.49% | 990 | 6.72 | 2,664 | 18.09 | 11,078 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Purranque | 20,705 | 1,459 | 14.2 | 13,265 | 64.07% | 10,354 | 50.01% | 5,810 | 3,111 | 5,854 | 3,579 | 1,729 | 7.49% | 1,391 | 6.72 | 3,745 | 18.09 | 15,569 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Puerto Octay | 10,236 | 1,796 | 5.7 | 3,403 | 33.25% | 5,391 | 52.67% | 3,310 | 1,917 | 3,692 | 1,914 | 655 | 7.49% | 688 | 6.72 | 1,851 | 18.09 | 7,697 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Fresia | 12,804 | 1,278 | 10.0 | 6,144 | 47.99% | 6,580 | 51.39% | 3,788 | 2,139 | 4,012 | 2,403 | 1,139 | 7.49% | 860 | 6.72 | 2,316 | 18.09 | 9,628 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Frutillar | 15,525 | 831 | 18.7 | 9,118 | 58.73% | 7,948 | 51.19% | 4,231 | 2,243 | 4,328 | 2,421 | 970 | 7.49% | 1,043 | 6.72 | 2,808 | 18.09 | 11,674 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Puerto Varas | 32,912 | 4,065 | 8.1 | 24,309 | 73.86% | 16,645 | 50.57% | 9,265 | 5,026 | 9,297 | 4,941 | 1,894 | 7.49% | 2,212 | 6.72 | 5,952 | 18.09 | 24,748 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Llanquihue | 16,337 | 421 | 38.8 | 12,728 | 77.91% | 8,141 | 49.83% | 4,444 | 2,514 | 4,771 | 2,506 | 1,031 | 7.49% | 1,098 | 6.72 | 2,955 | 18.09 | 12,285 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Los Muermos | 16,964 | 1,246 | 13.6 | 5,707 | 33.64% | 8,939 | 52.69% | 5,378 | 2,860 | 5,158 | 3,114 | 1,413 | 7.49% | 1,140 | 6.72 | 3,068 | 18.09 | 12,756 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Puerto Montt | 175,938 | 1,673 | 105.2 | 155,895 | 88.61% | 87,825 | 49.92% | 45,557 | 26,062 | 49,886 | 24,651 | 9,154 | 7.49% | 4,524 | 3.09 | 21,727 | 14.84 | 120,165 | 82.07 | 935.52 | 0 | 0 | 1 | 0 | 4.25% |
| Maullín | 15,580 | 861 | 18.1 | 6,896 | 44.26% | 8,146 | 52.28% | 6,794 | 3,241 | 6,456 | 3,350 | 1,311 | 7.49% | 1,047 | 6.72 | 2,818 | 18.09 | 11,715 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Calbuco | 31,070 | 591 | 52.6 | 12,165 | 39.15% | 15,906 | 51.19% | 9,494 | 4,473 | 9,457 | 4,841 | 2,401 | 7.49% | 2,088 | 6.72 | 5,619 | 18.09 | 23,363 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Cochamó | 4,363 | 3,911 | 1.1 | 0 | 0.00% | 2,506 | 57.44% | 1,513 | 734 | 1,552 | 849 | 359 | 7.49% | 293 | 6.72 | 789 | 18.09 | 3,281 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Ancud | 39,946 | 1,752 | 22.8 | 27,292 | 68.32% | 19,793 | 49.55% | 13,800 | 7,510 | 14,488 | 7,173 | 2,658 | 7.49% | 2,559 | 5.74 | 10,745 | 24.10 | 31,284 | 70.16 | 609.96 | 0 | 0 | 1 | 0 | 4.25% |
| Dalcahue | 10,693 | 1,239 | 8.6 | 4,933 | 46.13% | 5,420 | 50.69% | 2,553 | 1,402 | 2,863 | 1,382 | 785 | 7.49% | 719 | 6.72 | 1,934 | 18.09 | 8,041 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Quemchi | 8,689 | 440 | 19.7 | 1,665 | 19.16% | 4,525 | 52.08% | 2,205 | 1,225 | 2,300 | 1,470 | 848 | 7.49% | 584 | 6.72 | 1,571 | 18.09 | 6,534 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Castro | 39,366 | 428 | 92.1 | 29,148 | 74.04% | 19,325 | 49.09% | 9,776 | 5,446 | 10,036 | 5,458 | 2,657 | 7.49% | 2,645 | 6.72 | 7,119 | 18.09 | 29,601 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Quinchao | 8,976 | 161 | 55.9 | 3,452 | 38.46% | 4,417 | 49.21% | 2,556 | 1,622 | 2,482 | 1,610 | 896 | 7.49% | 603 | 6.72 | 1,623 | 18.09 | 6,749 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Curaco De Vélez | 3,403 | 80 | 42.5 | 0 | 0.00% | 1,642 | 48.25% | 682 | 448 | 905 | 586 | 382 | 7.49% | 229 | 6.72 | 615 | 18.09 | 2,559 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Chonchi | 12,572 | 1,362 | 9.2 | 4,588 | 36.49% | 6,453 | 51.33% | 3,254 | 1,897 | 3,723 | 1,939 | 963 | 7.49% | 845 | 6.72 | 2,274 | 18.09 | 9,453 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Puqueldón | 4,160 | 97 | 42.8 | 0 | 0.00% | 2,006 | 48.22% | 1,150 | 705 | 1,151 | 778 | 445 | 7.49% | 280 | 6.72 | 752 | 18.09 | 3,128 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Queilén | 5,138 | 333 | 15.4 | 1,912 | 37.21% | 2,663 | 51.83% | 1,582 | 853 | 1,486 | 840 | 460 | 7.49% | 345 | 6.72 | 929 | 18.09 | 3,864 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |

# Table A2.1: Data per Commune



| | | | | | | | | AGE GROUPS (5) | | | | | | | | | | | | | ECONOMIC ACTIVITY (9) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | POP (1) | AREA (2) | DEN | URB (3) | %URB | MEN (4) | %MEN | 0-14 | 15-24 | 25-44 | 45-64 | 65+ | NAT (6) | IND (7) | %IND | PNI (7) | %PNI | NP (7) | %NP | INC (8) | Trn | Min | Agr-Sil | Man | GDP (10) |
| Quellón | 21,823 | 3,244 | 6.7 | 13,656 | 62.58% | 11,595 | 53.13% | 6,337 | 3,573 | 6,664 | 2,597 | 901 | 7.49% | 1,467 | 6.72 | 3,947 | 18.09 | 16,410 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Hualaihué | 8,273 | 2,788 | 3.0 | 2,406 | 29.08% | 4,457 | 53.87% | 3,095 | 1,681 | 3,144 | 1,348 | 542 | 7.49% | 556 | 6.72 | 1,496 | 18.09 | 6,221 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Chaitén | 7,182 | 8,471 | 0.8 | 4,065 | 56.60% | 3,940 | 54.86% | 2,362 | 1,537 | 2,262 | 1,008 | 405 | 7.49% | 483 | 6.72 | 1,299 | 18.09 | 5,400 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Futaleufú | 1,826 | 1,280 | 1.4 | 1,153 | 63.14% | 954 | 52.25% | 460 | 225 | 535 | 344 | 119 | 7.49% | 123 | 6.72 | 330 | 18.09 | 1,373 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Palena | 1,690 | 2,764 | 0.6 | 0 | 0.00% | 904 | 53.49% | 334 | 185 | 415 | 301 | 151 | 7.49% | 114 | 6.72 | 306 | 18.09 | 1,271 | 75.19 | 764.24 | 0 | 0 | 1 | 0 | 4.25% |
| Guaitecas | 1,539 | 459 | 3.4 | 1,411 | 91.68% | 913 | 59.32% | 542 | 258 | 418 | 214 | 86 | 4.31% | 0 | 0.00 | 233 | 15.12 | 1,306 | 84.88 | 1,092.88 | 0 | 0 | 1 | 0 | 0.52% |
| Cisnes | 5,739 | 16,093 | 0.4 | 2,507 | 43.68% | 3,414 | 59.49% | 2,352 | 1,387 | 2,675 | 1,018 | 210 | 4.31% | 0 | 0.00 | 868 | 15.12 | 4,871 | 84.88 | 1,092.88 | 0 | 0 | 1 | 0 | 0.52% |
| Lago Verde | 1,062 | 4,503 | 0.2 | 0 | 0.00% | 655 | 61.68% | 303 | 211 | 475 | 303 | 94 | 4.31% | 0 | 0.00 | 161 | 15.12 | 901 | 84.88 | 1,092.88 | 0 | 0 | 1 | 0 | 0.52% |
| Aisén | 22,353 | 34,772 | 0.6 | 19,580 | 87.59% | 11,853 | 53.03% | 7,636 | 3,673 | 8,318 | 3,717 | 1,062 | 4.31% | 0 | 0.00 | 2,864 | 12.70 | 19,683 | 87.30 | 811.33 | 0 | 0 | 1 | 0 | 0.52% |
| Coihaique | 50,041 | 7,755 | 6.5 | 44,850 | 89.63% | 25,453 | 50.86% | 14,961 | 9,256 | 13,532 | 7,552 | 2,423 | 4.31% | 0 | 0.00 | 7,306 | 16.33 | 37,424 | 83.67 | 1,374.42 | 0 | 0 | 1 | 0 | 0.52% |
| Río Ibáñez | 2,477 | 3,699 | 0.7 | 0 | 0.00% | 1,357 | 54.78% | 718 | 346 | 617 | 484 | 220 | 4.31% | 0 | 0.00 | 0 | -2.91 | 1 | 102.91 | 1,092.88 | 0 | 0 | 1 | 0 | 0.52% |
| Chile Chico | 4,444 | 4,669 | 1.0 | 3,042 | 68.45% | 2,378 | 53.51% | 1,002 | 549 | 1,152 | 740 | 348 | 4.31% | 0 | 0.00 | 672 | 15.12 | 3,772 | 84.88 | 1,092.88 | 0 | 0 | 1 | 0 | 0.52% |
| Tortel | 507 | 21,347 | 0.0 | 0 | 0.00% | 322 | 63.51% | 136 | 104 | 238 | 70 | 19 | 4.31% | 0 | 0.00 | 77 | 15.12 | 430 | 84.88 | 1,092.88 | 0 | 0 | 1 | 0 | 0.52% |
| Cochrane | 2,867 | 8,500 | 0.3 | 2,217 | 77.33% | 1,555 | 54.24% | 1,146 | 709 | 1,148 | 640 | 193 | 4.31% | 0 | 0.00 | 433 | 15.12 | 2,434 | 84.88 | 1,092.88 | 0 | 0 | 1 | 0 | 0.52% |
| O'Higgins | 463 | 9,506 | 0.0 | 0 | 0.00% | 277 | 59.83% | 88 | 85 | 127 | 52 | 29 | 4.31% | 0 | 0.00 | 70 | 15.12 | 393 | 84.88 | 1,092.88 | 0 | 0 | 1 | 0 | 0.52% |
| Natales | 19,116 | 22,000 | 0.9 | 16,978 | 88.82% | 10,068 | 52.67% | 4,347 | 2,410 | 5,106 | 4,024 | 1,660 | 3.56% | 0 | 0.00 | 2,535 | 15.12 | 14,234 | 84.88 | 823.12 | 0 | 0 | 0 | 1 | 2.02% |
| Torres del Paine | 739 | 1,814 | 0.4 | 0 | 0.00% | 543 | 73.48% | 65 | 52 | 216 | 141 | 22 | 3.56% | 0 | 0.00 | 88 | 11.87 | 651 | 88.13 | 1,242.16 | 0 | 0 | 0 | 1 | 2.02% |
| Río Verde | 358 | 13,597 | 0.0 | 0 | 0.00% | 295 | 82.40% | 9 | 9 | 157 | 102 | 24 | 3.56% | 0 | 0.00 | 43 | 11.87 | 315 | 88.13 | 1,242.16 | 0 | 0 | 0 | 1 | 2.02% |
| Laguna Blanca | 663 | 6,000 | 0.1 | 0 | 0.00% | 563 | 84.92% | 96 | 93 | 509 | 259 | 34 | 3.56% | 0 | 0.00 | 79 | 11.87 | 584 | 88.13 | 1,242.16 | 0 | 0 | 0 | 1 | 2.02% |
| San Gregorio | 1,158 | 8,000 | 0.1 | 0 | 0.00% | 886 | 76.51% | 296 | 154 | 588 | 389 | 84 | 3.56% | 0 | 0.00 | 137 | 11.87 | 1,021 | 88.13 | 1,242.16 | 0 | 0 | 0 | 1 | 2.02% |
| Punta Arenas | 119,496 | 17,805 | 6.7 | 116,005 | 97.08% | 60,616 | 50.73% | 33,308 | 20,204 | 41,133 | 23,503 | 8,768 | 3.56% | 0 | 0.00 | 13,573 | 11.29 | 106,659 | 88.71 | 1,084.21 | 0 | 0 | 0 | 1 | 2.02% |
| Primavera | 1,016 | 7,000 | 0.1 | 0 | 0.00% | 735 | 72.34% | 194 | 122 | 605 | 332 | 36 | 3.56% | 0 | 0.00 | 121 | 11.87 | 895 | 88.13 | 1,242.16 | 0 | 0 | 0 | 1 | 2.02% |
| Porvenir | 5,465 | 7,500 | 0.7 | 4,734 | 86.62% | 3,307 | 60.51% | 1,268 | 726 | 1,218 | 959 | 384 | 3.56% | 0 | 0.00 | 646 | 15.71 | 3,465 | 84.29 | 1,819.14 | 0 | 0 | 0 | 1 | 2.02% |
| Timaukel | 423 | 8,500 | 0.0 | 0 | 0.00% | 376 | 88.89% | 56 | 33 | 63 | 58 | 13 | 3.56% | 0 | 0.00 | 50 | 11.87 | 373 | 88.13 | 1,242.16 | 0 | 0 | 0 | 1 | 2.02% |
| Navarino | 2,262 | 17,000 | 0.1 | 1,952 | 86.30% | 1,403 | 62.02% | 684 | 430 | 1,234 | 186 | 36 | 3.56% | 0 | 0.00 | 269 | 11.87 | 1,993 | 88.13 | 1,242.16 | 0 | 0 | 0 | 1 | 2.02% |
| Antártica | 130 | 23,081 | 0.0 | 0 | 0.00% | 115 | 88.46% | 25 | 3 | 98 | 5 | 0 | 3.56% | 0 | 0.00 | 15 | 11.87 | 115 | 88.13 | 1,242.16 | 0 | 0 | 0 | 1 | 2.02% |
| Tiltil | 14,755 | 653 | 22.6 | 8,161 | 55.31% | 7,609 | 51.57% | 4,679 | 2,276 | 4,263 | 2,327 | 1,019 | 8.24% | 461 | 3.25 | 1,518 | 10.69 | 12,220 | 86.06 | 726.41 | 1 | 0 | 0 | 0 | 47.76% |
| Colina | 77,815 | 971 | 80.1 | 62,811 | 80.72% | 41,004 | 52.69% | 25,278 | 14,444 | 26,257 | 10,283 | 2,780 | 8.24% | 4,279 | 5.92 | 10,735 | 14.85 | 57,261 | 79.23 | 848.51 | 1 | 0 | 0 | 0 | 47.76% |
| Lampa | 40,228 | 452 | 89.0 | 28,229 | 70.17% | 20,571 | 51.14% | 10,200 | 5,056 | 9,226 | 4,641 | 1,881 | 8.24% | 2,110 | 7.09 | 5,590 | 18.79 | 22,053 | 74.12 | 671.33 | 1 | 0 | 0 | 0 | 47.76% |
| Curacaví | 24,298 | 693 | 35.1 | 15,645 | 64.39% | 12,351 | 50.83% | 6,851 | 3,652 | 6,939 | 3,905 | 1,572 | 8.24% | 926 | 4.11 | 4,008 | 17.78 | 17,605 | 78.11 | 772.64 | 1 | 0 | 0 | 0 | 47.76% |
| Maria Pinto | 10,343 | 395 | 26.2 | 1,654 | 15.99% | 5,218 | 50.45% | 2,969 | 1,521 | 2,854 | 1,620 | 720 | 8.24% | 813 | 8.46 | 1,285 | 13.37 | 7,513 | 78.17 | 534.39 | 1 | 0 | 0 | 0 | 47.76% |
| Melipilla | 94,540 | 1,345 | 70.3 | 60,898 | 64.42% | 47,603 | 50.35% | 27,522 | 14,971 | 28,004 | 15,791 | 6,211 | 8.24% | 4,101 | 4.51 | 16,103 | 17.69 | 70,816 | 77.80 | 697.93 | 1 | 0 | 0 | 0 | 47.76% |
| San Pedro | 7,549 | 788 | 9.6 | 0 | 0.00% | 4,080 | 54.05% | 1,854 | 1,003 | 1,965 | 1,466 | 714 | 8.24% | 447 | 6.36 | 757 | 10.77 | 5,822 | 82.86 | 582.28 | 1 | 0 | 0 | 0 | 47.76% |
| Alhué | 4,435 | 845 | 5.2 | 2,593 | 58.47% | 2,343 | 52.83% | 1,324 | 630 | 1,387 | 698 | 390 | 8.24% | 276 | 6.00 | 907 | 19.71 | 3,418 | 74.29 | 415.06 | 1 | 0 | 0 | 0 | 47.76% |
| Paine | 50,028 | 678 | 73.8 | 31,622 | 63.21% | 25,571 | 51.11% | 13,754 | 7,834 | 14,244 | 7,261 | 2,547 | 8.24% | 2,144 | 4.84 | 6,937 | 15.66 | 35,227 | 79.50 | 1,085.34 | 1 | 0 | 0 | 0 | 47.76% |
| Buin | 63,419 | 214 | 296.2 | 53,506 | 84.37% | 31,440 | 49.58% | 19,466 | 10,323 | 19,107 | 9,084 | 3,525 | 8.24% | 2,041 | 3.41 | 11,736 | 19.59 | 46,143 | 77.01 | 792.90 | 1 | 0 | 0 | 0 | 47.76% |
| San Bernardo | 246,762 | 155 | 1,591.0 | 241,138 | 97.72% | 121,535 | 49.25% | 78,733 | 41,657 | 78,652 | 37,887 | 12,706 | 8.24% | 9,194 | 3.80 | 38,982 | 16.13 | 193,466 | 80.06 | 752.06 | 1 | 0 | 0 | 0 | 47.76% |
| Calera de Tango | 18,235 | 73 | 248.8 | 9,932 | 54.47% | 9,243 | 50.69% | 4,311 | 2,306 | 4,506 | 2,297 | 726 | 8.24% | 392 | 2.79 | 1,106 | 7.87 | 12,550 | 89.34 | 840.07 | 1 | 0 | 0 | 0 | 47.76% |
| Padre Hurtado | 38,768 | 81 | 479.8 | 34,257 | 88.36% | 19,367 | 49.96% | 9,806 | 5,740 | 11,539 | 6,206 | 2,341 | 8.24% | 1,630 | 4.68 | 4,706 | 13.52 | 28,474 | 81.80 | 647.19 | 1 | 0 | 0 | 0 | 47.76% |
| Peñaflor | 66,619 | 69 | 962.7 | 63,209 | 94.88% | 32,671 | 49.04% | 15,902 | 9,025 | 17,874 | 10,529 | 3,945 | 8.24% | 3,368 | 5.96 | 9,777 | 17.30 | 43,368 | 76.74 | 768.37 | 1 | 0 | 0 | 0 | 47.76% |
| El Monte | 26,459 | 118 | 225.0 | 22,284 | 84.22% | 13,334 | 50.39% | 7,080 | 3,930 | 7,261 | 3,993 | 1,688 | 8.24% | 3,643 | 15.37 | 6,086 | 25.68 | 13,966 | 58.94 | 550.12 | 1 | 0 | 0 | 0 | 47.76% |
| Talagante | 59,805 | 126 | 476.5 | 49,957 | 83.53% | 29,468 | 49.27% | 17,128 | 9,642 | 17,390 | 8,669 | 3,225 | 8.24% | 2,882 | 5.31 | 10,647 | 19.61 | 40,778 | 75.09 | 806.51 | 1 | 0 | 0 | 0 | 47.76% |
| Isla de Maipo | 25,798 | 189 | 136.7 | 18,865 | 73.13% | 13,095 | 50.76% | 6,535 | 3,720 | 6,772 | 3,685 | 1,660 | 8.24% | 737 | 3.33 | 4,056 | 18.32 | 17,346 | 78.35 | 625.49 | 1 | 0 | 0 | 0 | 47.76% |
| San José de Maipo | 13,376 | 4,995 | 2.7 | 9,311 | 69.61% | 6,947 | 51.94% | 3,687 | 1,900 | 3,744 | 2,317 | 935 | 8.24% | 564 | 4.65 | 1,065 | 8.79 | 10,492 | 86.56 | 1,384.97 | 1 | 0 | 0 | 0 | 47.76% |
| Puente Alto | 492,915 | 88 | 5,588.6 | 492,603 | 99.94% | 240,862 | 48.86% | 140,315 | 62,396 | 138,179 | 53,313 | 12,774 | 8.24% | 16,768 | 4.34 | 58,884 | 15.25 | 310,597 | 80.41 | 789.28 | 1 | 0 | 0 | 0 | 47.76% |
| Pirque | 16,565 | 445 | 37.2 | 9,651 | 58.26% | 8,384 | 50.61% | 4,291 | 2,056 | 4,155 | 2,156 | 741 | 8.24% | 459 | 3.60 | 663 | 5.21 | 11,611 | 91.19 | 1,347.00 | 1 | 0 | 0 | 0 | 47.76% |
| Lo Barnechea | 74,749 | 1,024 | 73.0 | 72,496 | 96.99% | 34,901 | 46.69% | 20,008 | 11,881 | 22,823 | 12,143 | 2,658 | 8.24% | 1,652 | 2.72 | 3,524 | 5.81 | 55,469 | 91.47 | 3,526.55 | 1 | 0 | 0 | 0 | 47.76% |
| Vitacura | 81,499 | 28 | 2,879.8 | 81,499 | 100.00% | 35,118 | 43.09% | 17,874 | 13,879 | 25,693 | 19,102 | 8,407 | 8.24% | 0 | 0.00 | 553 | 0.74 | 73,805 | 99.26 | 3,422.74 | 1 | 0 | 0 | 0 | 47.76% |
| Las Condes | 249,893 | 99 | 2,514.0 | 249,893 | 100.00% | 110,916 | 44.39% | 50,230 | 36,555 | 68,610 | 48,415 | 24,624 | 8.24% | 1,362 | 0.63 | 1,764 | 0.81 | 214,210 | 98.56 | 3,526.55 | 1 | 0 | 0 | 0 | 47.76% |
| La Reina | 96,762 | 23 | 4,135.1 | 96,762 | 100.00% | 44,293 | 45.78% | 25,262 | 16,922 | 30,843 | 20,488 | 8,493 | 8.24% | 1,376 | 1.44 | 1,205 | 1.26 | 92,712 | 97.29 | 3,480.39 | 1 | 0 | 0 | 0 | 47.76% |
| Peñalolén | 216,060 | 54 | 3,986.3 | 216,060 | 100.00% | 105,528 | 48.84% | 65,283 | 33,166 | 68,807 | 33,118 | 10,023 | 8.24% | 8,839 | 4.26 | 31,991 | 15.44 | 166,430 | 80.30 | 954.58 | 1 | 0 | 0 | 0 | 47.76% |
| La Florida | 365,674 | 71 | 5,164.9 | 365,563 | 99.97% | 176,245 | 48.20% | 123,205 | 68,048 | 142,150 | 72,275 | 20,246 | 8.24% | 4,065 | 0.97 | 36,069 | 8.62 | 378,189 | 90.41 | 1,258.10 | 1 | 0 | 0 | 0 | 47.76% |
| Huechuraba | 74,070 | 45 | 1,653.3 | 74,070 | 100.00% | 36,433 | 49.19% | 19,983 | 10,851 | 19,585 | 11,966 | 3,383 | 8.24% | 3,803 | 5.83 | 11,982 | 18.36 | 49,490 | 75.82 | 865.78 | 1 | 0 | 0 | 0 | 47.76% |
| Recoleta | 148,220 | 16 | 9,149.4 | 148,220 | 100.00% | 72,314 | 48.79% | 44,129 | 26,634 | 48,566 | 31,948 | 14,302 | 8.24% | 4,445 | 2.72 | 16,982 | 10.40 | 141,802 | 86.87 | 789.20 | 1 | 0 | 0 | 0 | 47.76% |
| Providencia | 120,874 | 14 | 8,394.0 | 120,874 | 100.00% | 53,082 | 43.92% | 17,892 | 15,049 | 32,307 | 23,627 | 18,957 | 8.24% | 0 | 0.00 | 0 | 0.00 | 99,029 | 100.00 | 3,422.74 | 1 | 0 | 0 | 0 | 47.76% |
| Ñuñoa | 163,511 | 17 | 9,675.2 | 163,511 | 100.00% | 73,215 | 44.78% | 38,642 | 25,667 | 50,359 | 35,115 | 24,830 | 8.24% | 3,360 | 2.00 | 1,228 | 0.73 | 163,529 | 97.27 | 2,477.06 | 1 | 0 | 0 | 0 | 47.76% |
| Macul | 112,535 | 13 | 8,723.6 | 112,535 | 100.00% | 53,667 | 47.69% | 32,889 | 18,952 | 40,185 | 23,679 | 10,382 | 8.24% | 2,774 | 2.24 | 13,578 | 10.97 | 107,445 | 86.79 | 1,197.32 | 1 | 0 | 0 | 0 | 47.76% |
| Conchalí | 133,256 | 11 | 12,453.8 | 133,256 | 100.00% | 64,973 | 48.76% | 40,410 | 23,507 | 45,198 | 27,286 | 13,325 | 8.24% | 4,305 | 2.88 | 14,861 | 9.93 | 130,531 | 87.20 | 785.48 | 1 | 0 | 0 | 0 | 47.76% |
| Independencia | 65,479 | 7 | 8,848.5 | 65,479 | 100.00% | 30,633 | 46.78% | 15,984 | 11,012 | 21,076 | 15,314 | 9,010 | 8.24% | 887 | 1.26 | 3,465 | 4.90 | 66,306 | 93.84 | 1,111.30 | 1 | 0 | 0 | 0 | 47.76% |
| Santiago | 200,792 | 22 | 8,963.9 | 200,792 | 100.00% | 99,155 | 49.38% | 43,719 | 36,955 | 71,304 | 48,362 | 29,256 | 8.24% | 854 | 0.40 | 9,412 | 4.44 | 201,904 | 95.16 | 1,260.17 | 1 | 0 | 0 | 0 | 47.76% |
| San Joaquín | 97,625 | 10 | 10,064.4 | 97,625 | 100.00% | 46,708 | 47.84% | 28,973 | 15,330 | 31,269 | 19,800 | 10,354 | 8.24% | 2,151 | 2.03 | 9,972 | 9.40 | 93,992 | 88.58 | 876.00 | 1 | 0 | 0 | 0 | 47.76% |
| La Granja | 132,520 | 10 | 13,120.8 | 132,520 | 100.00% | 64,750 | 48.86% | 44,825 | 25,654 | 48,430 | 23,409 | 9,465 | 8.24% | 6,646 | 4.46 | 15,865 | 10.65 | 126,496 | 84.89 | 761.21 | 1 | 0 | 0 | 0 | 47.76% |
| San Ramón | 94,906 | 7 | 14,600.9 | 94,906 | 100.00% | 46,596 | 49.10% | 27,866 | 16,155 | 32,641 | 18,688 | 6,471 | 8.24% | 3,658 | 3.60 | 22,048 | 21.69 | 75,941 | 74.71 | 690.92 | 1 | 0 | 0 | 0 | 47.76% |
| La Pintana | 190,085 | 31 | 6,211.9 | 190,085 | 100.00% | 94,963 | 49.96% | 85,658 | 41,251 | 78,171 | 30,610 | 6,331 | 8.24% | 22,829 | 9.56 | 51,005 | 21.35 | 165,028 | 69.09 | 577.41 | 1 | 0 | 0 | 0 | 47.76% |
| San Miguel | 78,872 | 10 | 8,302.3 | 78,872 | 100.00% | 37,836 | 47.97% | 17,113 | 12,139 | 23,761 | 16,392 | 9,288 | 8.24% | 857 | 1.14 | 3,185 | 4.25 | 70,825 | 94.60 | 1,297.53 | 1 | 0 | 0 | 0 | 47.76% |
| La Cisterna | 85,118 | 10 | 8,511.8 | 85,118 | 100.00% | 40,651 | 47.76% | 22,506 | 14,371 | 27,944 | 18,994 | 9,301 | 8.24% | 960 | 1.05 | 4,119 | 4.49 | 86,603 | 94.46 | 1,139.15 | 1 | 0 | 0 | 0 | 47.76% |

Appendix 2 (cont.)

# Table A2.1: Data per Commune



| Commune | POP (1) | AREA (2) | DEN | URB (3) | %URB | MEN (4) | %MEN | AGE GROUPS (5) 0-14 | 15-24 | 25-44 | 45-64 | 65+ | NAT (6) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| El Bosque | 175,594 | 14 | 12,453.5 | 175,594 | 100.00% | 86,435 | 49.22% | 58,701 | 31,014 | 59,299 | 33,259 | 11,089 | 8.24% |
| Pedro Aguirre Cerda | 114,560 | 10 | 11,810.3 | 114,560 | 100.00% | 55,382 | 48.34% | 29,834 | 18,371 | 35,253 | 21,836 | 12,436 | 8.24% |
| Lo Espejo | 112,800 | 7 | 15,666.7 | 112,800 | 100.00% | 55,478 | 49.18% | 33,084 | 18,302 | 35,612 | 19,377 | 9,660 | 8.24% |
| Quilicura | 126,518 | 58 | 2,200.3 | 125,999 | 99.59% | 62,421 | 49.34% | 17,558 | 9,538 | 18,118 | 8,221 | 1,926 | 8.24% |
| Renca | 133,518 | 24 | 5,517.3 | 133,518 | 100.00% | 66,253 | 49.62% | 46,501 | 28,145 | 47,285 | 25,134 | 7,607 | 8.24% |
| Quinta Normal | 104,012 | 12 | 8,388.1 | 104,012 | 100.00% | 50,509 | 48.56% | 27,135 | 16,608 | 31,791 | 20,891 | 10,894 | 8.24% |
| Cerro Navia | 148,312 | 11 | 13,361.4 | 148,312 | 100.00% | 72,921 | 49.17% | 50,173 | 28,336 | 52,162 | 28,176 | 9,591 | 8.24% |
| Lo Prado | 104,316 | 7 | 15,569.6 | 104,316 | 100.00% | 50,608 | 48.51% | 31,215 | 18,069 | 37,204 | 21,610 | 7,779 | 8.24% |
| Estación Central | 130,394 | 14 | 9,247.8 | 130,394 | 100.00% | 63,939 | 49.04% | 33,104 | 19,634 | 42,936 | 26,011 | 12,882 | 8.24% |
| Cerrillos | 71,906 | 21 | 3,424.1 | 71,906 | 100.00% | 34,961 | 48.62% | 19,617 | 13,090 | 24,975 | 13,910 | 5,541 | 8.24% |
| Pudahuel | 195,653 | 197 | 991.1 | 192,258 | 98.26% | 96,328 | 49.23% | 54,273 | 27,952 | 54,244 | 24,041 | 7,060 | 8.24% |
| Maipú | 468,390 | 133 | 3,521.7 | 464,882 | 99.25% | 227,285 | 48.52% | 110,843 | 56,408 | 123,737 | 53,463 | 14,369 | 8.24% |

| Commune | IND (7) | %IND | PNI (7) | %PNI | NP (7) | %NP | INC (8) | ECONOMIC ACTIVITY (9) Tra | Min | Agr-Sil | Man | GDP (10) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| El Bosque | 13,004 | 6.81 | 45,763 | 23.97 | 132,159 | 69.22 | 718.04 | 1 | 0 | 0 | 0 | 47.76% |
| Pedro Aguirre Cerda | 0 | 0.00 | 19,333 | 16.31 | 99,203 | 83.69 | 783.29 | 1 | 0 | 0 | 0 | 47.76% |
| Lo Espejo | 11,148 | 9.59 | 25,406 | 21.85 | 79,705 | 68.56 | 599.18 | 1 | 0 | 0 | 0 | 47.76% |
| Quilicura | 3,708 | 6.80 | 8,464 | 15.52 | 42,352 | 77.68 | 787.17 | 1 | 0 | 0 | 0 | 47.76% |
| Renca | 5,095 | 3.35 | 23,296 | 15.31 | 123,797 | 81.34 | 706.12 | 1 | 0 | 0 | 0 | 47.76% |
| Quinta Normal | 3,591 | 3.35 | 9,609 | 8.96 | 94,053 | 87.69 | 812.52 | 1 | 0 | 0 | 0 | 47.76% |
| Cerro Navia | 7,430 | 4.44 | 37,162 | 22.22 | 122,634 | 73.33 | 602.79 | 1 | 0 | 0 | 0 | 47.76% |
| Lo Prado | 3,297 | 2.86 | 11,367 | 9.88 | 100,436 | 87.26 | 1,016.86 | 1 | 0 | 0 | 0 | 47.76% |
| Estación Central | 6,559 | 4.97 | 14,541 | 11.02 | 110,871 | 84.01 | 831.03 | 1 | 0 | 0 | 0 | 47.76% |
| Cerrillos | 1,325 | 1.76 | 7,412 | 9.85 | 66,533 | 88.39 | 983.64 | 1 | 0 | 0 | 0 | 47.76% |
| Pudahuel | 7,588 | 4.68 | 23,537 | 14.53 | 130,860 | 80.79 | 786.20 | 1 | 0 | 0 | 0 | 47.76% |
| Maipú | 7,597 | 2.17 | 24,151 | 6.90 | 318,496 | 90.94 | 999.95 | 1 | 0 | 0 | 0 | 47.76% |

Note:
(1): Populatio
(2): Area (km
(3): Urban Po
(4): Male Pop
(5): Age Grou
(6): Native Po
(7): Indigent,
(8): Income (U
(9): Economic
(10): Gross D
(11): Foreign
(12): Exports:
(13): Construc
(14): Vehicles
(15): Employr
(16): Labour I
(17): Unempl
(18): Years of
(19): Public P
(20): Number
(21): Illiterate
(22): Number
(23): Climate
(24): Geograp
(25): Waste G
(26): Waste G
(27): Per Capi
(28): Existenc

# Table A2.1: Data per Commune

| | | | | | | | | | | | | | | Climate (23) | | | | Geography (24) | | | | | | | DISPOSAL SITE? (28) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | FI (11) | EXP (12) | CON (13) | VEH (14) | EMP (15) | %LF (16) | UR (17) | EDU (18) | PP (19) | LIB (20) | IR (21) | HOU (22) | HD | WD | MT | MR | CS | C | M | V | WAS01 (25) | WAS02 (26) | %VW | PCWG02 (27) | Y | N |
| Arica | 0.39% | 6.78% | 91,176 | 29,185 | 2.66% | 57.59 | 8.33 | 10.1 | 369 | 41 | 1.4 | 50,245 | 3.69 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 3,000.0 | 3,000.0 | 0.00 | 0.53 | 1 | 0 |
| General Lagos | 0.39% | 6.78% | 36,337 | 3,002 | 2.66% | 71.66 | 8.33 | 4.7 | 0 | 0 | 27.7 | 459 | 2.57 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0.6 | 0.6 | 0.00 | 0.02 | 1 | 0 |
| Putre | 0.39% | 6.78% | 1,069 | 3,081 | 2.66% | 74.48 | 8.33 | 5.9 | 0 | 2 | 21.3 | 1,195 | 1.65 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 4.0 | 4.0 | 0.00 | 0.07 | 1 | 0 |
| Camarones | 0.39% | 6.78% | 36,337 | 1,423 | 2.66% | 75.64 | 8.33 | 6.3 | 0 | 0 | 15.9 | 669 | 1.82 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 3.0 | 3.0 | 0.00 | 0.08 | 1 | 0 |
| Huara | 0.39% | 6.78% | 829 | 295 | 2.66% | 59.08 | 8.33 | 7.5 | 0 | 0 | 6.1 | 2,005 | 1.30 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 16.0 | 16.0 | 0.00 | 0.20 | 1 | 0 |
| Camiña | 0.39% | 6.78% | 375 | 143 | 2.66% | 72.13 | 8.33 | 6.3 | 0 | 0 | 8.6 | 806 | 1.58 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 8.0 | 8.0 | 0.00 | 0.21 | 1 | 0 |
| Colchane | 0.39% | 6.78% | 36,337 | 811 | 2.66% | 48.84 | 8.33 | 5.2 | 0 | 0 | 23.1 | 1,355 | 1.22 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2.0 | 0.0 | -1.00 | 0.00 | 1 | 0 |
| Iquique | 0.39% | 6.78% | 140,088 | 48,903 | 2.66% | 53.56 | 8.33 | 10.8 | 488 | 19 | 1.2 | 61,054 | 3.54 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 6,600.0 | 6,600.0 | 0.00 | 1.00 | 1 | 0 |
| Pozo Almonte | 0.39% | 6.78% | 3,940 | 1,715 | 2.66% | 50.69 | 8.33 | 9.3 | 0 | 1 | 3.4 | 5,251 | 2.06 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 15.0 | 15.0 | 0.00 | 0.05 | 1 | 0 |
| Pica | 0.39% | 6.78% | 16,883 | 636 | 2.66% | 56.60 | 8.33 | 8.7 | 0 | 4 | 4.1 | 1,604 | 3.85 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 10.0 | 10.0 | 0.00 | 0.05 | 1 | 0 |
| Tocopilla | 73.47% | 24.91% | 5,316 | 3,082 | 2.91% | 48.09 | 9.25 | 9.4 | 0 | 8 | 1.8 | 7,370 | 3.25 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 903.9 | 750.0 | -0.17 | 1.03 | 1 | 0 |
| María Elena | 73.47% | 24.91% | 54,178 | 1,437 | 2.91% | 54.57 | 9.25 | 9.3 | 0 | 2 | 3.5 | 2,694 | 2.80 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 283.8 | 300.0 | 0.06 | 1.31 | 1 | 0 |
| Calama | 73.47% | 24.91% | 64,969 | 25,943 | 2.91% | 53.79 | 9.25 | 10.0 | 106 | 24 | 3.1 | 33,545 | 4.13 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2,125.0 | 3,300.0 | 0.55 | 0.78 | 1 | 0 |
| Ollagüe | 73.47% | 24.91% | 337 | 19 | 2.91% | 54.57 | 9.25 | 9.3 | 0 | 1 | 3.5 | 290 | 1.10 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 5.0 | 1.6 | -0.68 | 0.17 | 1 | 0 |
| Mejillones | 73.47% | 24.91% | 12,661 | 1,894 | 2.91% | 54.58 | 9.25 | 9.3 | 0 | 1 | 2.2 | 2,700 | 3.12 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 500.0 | 1,444.0 | 1.89 | 5.64 | 1 | 0 |
| Sierra Gorda | 73.47% | 24.91% | 258 | 1,354 | 2.91% | 54.57 | 9.25 | 9.3 | 0 | 2 | 3.5 | 479 | 4.92 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 24.0 | 42.0 | 0.75 | 0.59 | 1 | 0 |
| San Pedro de Atacama | 73.47% | 24.91% | 193 | 515 | 2.91% | 68.13 | 9.25 | 7.4 | 0 | 2 | 10.3 | 2,072 | 2.40 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 58.3 | 32.5 | -0.44 | 0.22 | 1 | 0 |
| Antofagasta | 73.47% | 24.91% | 347,252 | 46,884 | 2.91% | 51.62 | 9.25 | 10.9 | 726 | 39 | 0.3 | 74,482 | 3.99 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 15,651.0 | 18,331.0 | 0.17 | 2.03 | 1 | 0 |
| Taltal | 73.47% | 24.91% | 2,438 | 965 | 2.91% | 51.21 | 9.25 | 8.8 | 0 | 2 | 3.0 | 3,338 | 3.33 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 251.6 | 1,607.6 | 5.39 | 4.76 | 1 | 0 |
| Chañaral | 0.23% | 5.07% | 7,409 | 3,154 | 1.85% | 53.17 | 7.93 | 9.0 | 0 | 3 | 5.1 | 4,961 | 2.73 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 330.0 | 330.0 | 0.00 | 0.80 | 1 | 0 |
| Diego de Almagro | 0.23% | 5.07% | 9,070 | 3,278 | 1.85% | 51.96 | 7.93 | 9.9 | 62 | 4 | 4.9 | 6,529 | 2.85 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 120.0 | 288.0 | 1.40 | 0.51 | 1 | 0 |
| Caldera | 0.23% | 5.07% | 7,918 | 1,720 | 1.85% | 57.31 | 7.93 | 9.2 | 0 | 4 | 2.9 | 7,366 | 1.86 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 250.0 | 750.0 | 2.00 | 1.80 | 1 | 0 |
| Copiapó | 0.23% | 5.07% | 162,672 | 17,241 | 1.85% | 54.04 | 7.93 | 10.0 | 320 | 20 | 3.3 | 36,015 | 3.58 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 5,000.0 | 5,000.0 | 0.00 | 1.27 | 1 | 0 |
| Tierra Amarilla | 0.23% | 5.07% | 14,238 | 2,730 | 1.85% | 58.70 | 7.93 | 8.6 | 0 | 4 | 4.4 | 3,326 | 3.87 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 165.0 | 120.0 | -0.27 | 0.31 | 1 | 0 |
| Huasco | 0.23% | 5.07% | 4,435 | 1,504 | 1.85% | 46.05 | 7.93 | 9.2 | 0 | 4 | 3.5 | 3,138 | 2.53 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 90.0 | 90.0 | 0.00 | 0.37 | 1 | 0 |
| Freirina | 0.23% | 5.07% | 389 | 482 | 1.85% | 49.22 | 7.93 | 7.7 | 0 | 1 | 8.0 | 1,990 | 2.85 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 80.0 | 80.0 | 0.00 | 0.46 | 1 | 0 |
| Vallenar | 0.23% | 5.07% | 25,222 | 6,057 | 1.85% | 52.85 | 7.93 | 9.1 | 62 | 13 | 4.4 | 14,030 | 3.42 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 615.0 | 1,560.0 | 1.54 | 1.07 | 1 | 0 |
| Alto del Carmen | 0.23% | 5.07% | 3,208 | 719 | 1.85% | 55.53 | 7.93 | 6.8 | 0 | 1 | 13.1 | 2,050 | 2.36 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 3.5 | 3.5 | 0.00 | 0.02 | 1 | 0 |
| La Higuera | 0.00% | 4.32% | 4,689 | 4,176 | 3.59% | 58.10 | 8.20 | 6.1 | 9 | 1 | 15.2 | 1,814 | 2.05 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 32.5 | 39.5 | 0.22 | 0.35 | 1 | 0 |
| La Serena | 0.00% | 4.32% | 137,441 | 23,607 | 3.59% | 58.62 | 8.20 | 11.0 | 294 | 32 | 2.5 | 47,005 | 3.41 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 3,729.2 | 5,751.8 | 0.54 | 1.18 | 1 | 0 |
| Vicuña | 0.00% | 4.32% | 20,604 | 2,077 | 3.59% | 58.13 | 8.20 | 7.9 | 0 | 2 | 7.1 | 8,200 | 2.93 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 584.5 | 584.5 | 0.00 | 0.80 | 1 | 0 |
| Coquimbo | 0.00% | 4.32% | 116,391 | 14,081 | 3.59% | 57.78 | 8.20 | 9.7 | 0 | 9 | 4.6 | 50,335 | 3.24 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 3,735.3 | 5,808.0 | 0.55 | 1.17 | 1 | 0 |
| Andacollo | 0.00% | 4.32% | 536 | 1,010 | 3.59% | 51.32 | 8.20 | 7.9 | 0 | 2 | 7.1 | 3,478 | 2.96 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 200.0 | 90.5 | -0.55 | 0.29 | 1 | 0 |
| RíoHurtado | 0.00% | 4.32% | 1,207 | 1,669 | 3.59% | 49.80 | 8.20 | 6.3 | 0 | 0 | 11.7 | 2,076 | 2.30 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 60.0 | 45.0 | -0.25 | 0.31 | 1 | 0 |
| Paihuano | 0.00% | 4.32% | 1,908 | 415 | 3.59% | 56.12 | 8.20 | 8.1 | 0 | 0 | 5.6 | 1,833 | 2.27 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 95.5 | 116.2 | 0.22 | 0.92 | 0 | 1 |
| Ovalle | 0.00% | 4.32% | 89,044 | 11,173 | 3.59% | 52.49 | 8.20 | 8.9 | 267 | 11 | 5.2 | 29,468 | 3.33 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1,625.0 | 1,957.0 | 0.20 | 0.66 | 1 | 0 |
| Punitaqui | 0.00% | 4.32% | 6,420 | 1,479 | 3.59% | 46.16 | 8.20 | 7.1 | 0 | 1 | 11.8 | 3,712 | 2.57 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 240.0 | 112.0 | -0.53 | 0.39 | 1 | 0 |
| Monte Patria | 0.00% | 4.32% | 29,166 | 1,625 | 3.59% | 55.29 | 8.20 | 6.6 | 0 | 2 | 12.3 | 10,894 | 2.78 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 600.0 | 360.0 | -0.40 | 0.39 | 1 | 0 |
| Combarbalá | 0.00% | 4.32% | 11,844 | 956 | 3.59% | 43.74 | 8.20 | 7.0 | 0 | 2 | 11.3 | 5,215 | 2.59 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 250.0 | 180.0 | -0.28 | 0.44 | 1 | 0 |
| Canela | 0.00% | 4.32% | 1,797 | 1,199 | 3.59% | 48.15 | 8.20 | 6.1 | 0 | 1 | 16.7 | 3,938 | 2.38 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 150.0 | 150.0 | 0.00 | 0.53 | 1 | 0 |
| Illapel | 0.00% | 4.32% | 23,624 | 2,694 | 3.59% | 47.97 | 8.20 | 8.4 | 0 | 6 | 6.2 | 9,854 | 3.08 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 540.0 | 540.0 | 0.00 | 0.58 | 1 | 0 |
| Los Vilos | 0.00% | 4.32% | 29,325 | 2,592 | 3.59% | 55.70 | 8.20 | 7.9 | 12 | 2 | 6.4 | 7,516 | 2.32 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 300.0 | 400.0 | 0.33 | 0.75 | 1 | 0 |
| Salamanca | 0.00% | 4.32% | 72,896 | 1,946 | 3.59% | 49.32 | 8.20 | 7.1 | 0 | 2 | 12.0 | 7,483 | 3.27 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 540.0 | 540.0 | 0.00 | 0.72 | 1 | 0 |
| La Ligua | 0.07% | 8.24% | 12,663 | 4,990 | 9.44% | 60.13 | 10.57 | 8.9 | 0 | 4 | 5.8 | 11,236 | 2.85 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 469.4 | 460.6 | -0.02 | 0.47 | 0 | 1 |
| Petorca | 0.07% | 8.24% | 2,319 | 1,075 | 9.44% | 49.55 | 10.57 | 7.9 | 0 | 1 | 11.4 | 3,297 | 2.86 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 124.0 | 136.0 | 0.10 | 0.47 | 1 | 0 |
| Cabildo | 0.07% | 8.24% | 4,828 | 2,054 | 9.44% | 56.42 | 10.57 | 7.9 | 0 | 1 | 9.5 | 5,402 | 3.50 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 248.0 | 273.0 | 0.10 | 0.47 | 1 | 0 |
| Putaendo | 0.07% | 8.24% | 9,782 | 876 | 9.44% | 49.44 | 10.57 | 7.8 | 0 | 1 | 11.9 | 4,489 | 3.26 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 240.2 | 540.0 | 1.25 | 1.21 | 0 | 1 |
| San Esteban | 0.07% | 8.24% | 24,719 | 2,755 | 9.44% | 52.04 | 10.57 | 8.5 | 0 | 1 | 6.5 | 4,575 | 3.15 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 272.7 | 408.0 | 0.50 | 0.93 | 1 | 0 |
| Los Andes | 0.07% | 8.24% | 32,636 | 8,932 | 9.44% | 56.39 | 10.57 | 10.4 | 0 | 5 | 2.7 | 17,628 | 3.41 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1,139.8 | 1,683.0 | 0.48 | 0.92 | 0 | 1 |
| Papudo | 0.07% | 8.24% | 3,186 | 1,025 | 9.44% | 56.46 | 10.57 | 8.4 | 0 | 0 | 5.2 | 3,033 | 1.52 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 67.6 | 66.7 | -0.01 | 0.48 | 1 | 0 |
| Zapallar | 0.07% | 8.24% | 18,417 | 2,996 | 9.44% | 55.05 | 10.57 | 8.0 | 0 | 0 | 4.5 | 3,888 | 1.46 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 83.0 | 78.8 | -0.05 | 0.46 | 0 | 1 |
| Puchuncaví | 0.07% | 8.24% | 29,120 | 2,069 | 9.44% | 55.45 | 10.57 | 8.0 | 0 | 3 | 8.0 | 10,209 | 1.27 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 155.0 | 359.0 | 1.32 | 0.91 | 1 | 0 |
| Nogales | 0.07% | 8.24% | 884 | 2,489 | 9.44% | 52.67 | 10.57 | 8.3 | 0 | 2 | 6.4 | 6,012 | 3.60 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 427.7 | 370.1 | -0.13 | 0.56 | 0 | 1 |
| Catemu | 0.07% | 8.24% | 4,845 | 1,200 | 9.44% | 56.46 | 10.57 | 8.1 | 0 | 1 | 6.1 | 3,691 | 3.28 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 198.6 | 432.0 | 1.18 | 1.17 | 0 | 1 |
| San Felipe | 0.07% | 8.24% | 28,584 | 8,661 | 9.44% | 56.07 | 10.57 | 10.0 | 0 | 11 | 3.0 | 18,976 | 3.38 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1,051.6 | 2,376.0 | 1.26 | 1.22 | 1 | 0 |
| Santa María | 0.07% | 8.24% | 1,684 | 2,302 | 9.44% | 60.73 | 10.57 | 8.8 | 0 | 1 | 6.6 | 3,899 | 3.29 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 155.0 | 420.0 | 1.71 | 1.08 | 1 | 0 |
| Quintero | 0.07% | 8.24% | 18,171 | 2,626 | 9.44% | 51.86 | 10.57 | 9.8 | 0 | 3 | 2.8 | 11,084 | 1.91 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 310.0 | 587.0 | 0.89 | 0.91 | 1 | 0 |
| La Cruz | 0.07% | 8.24% | 11,143 | 2,214 | 9.44% | 62.39 | 10.57 | 10.0 | 0 | 1 | 4.1 | 3,867 | 3.32 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 71.6 | 236.4 | 2.30 | 0.60 | 0 | 1 |
| Calera | 0.07% | 8.24% | 8,190 | 5,671 | 9.44% | 58.27 | 10.57 | 9.1 | 0 | 7 | 4.2 | 14,357 | 3.45 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 978.7 | 854.1 | -0.13 | 0.57 | 0 | 1 |
| Hijuelas | 0.07% | 8.24% | 4,555 | 1,935 | 9.44% | 60.52 | 10.57 | 7.4 | 0 | 2 | 9.6 | 4,645 | 3.45 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 316.6 | 284.7 | -0.10 | 0.58 | 0 | 1 |
| Panquehue | 0.07% | 8.24% | 621 | 595 | 9.44% | 57.84 | 10.57 | 7.9 | 0 | 0 | 7.4 | 1,850 | 3.55 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 107.7 | 252.0 | 1.34 | 1.26 | 0 | 1 |
| Rinconada | 0.07% | 8.24% | 967 | 1,878 | 9.44% | 56.36 | 10.57 | 8.0 | 0 | 1 | 8.9 | 21,000 | 0.32 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 126.7 | 178.5 | 0.41 | 0.88 | 0 | 1 |
| Calle Larga | 0.07% | 8.24% | 5,972 | 1,280 | 9.44% | 54.21 | 10.57 | 8.2 | 0 | 1 | 7.6 | 2,822 | 3.68 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 196.8 | 280.5 | 0.43 | 0.89 | 0 | 1 |
| Llaillay | 0.07% | 8.24% | 8,681 | 2,310 | 9.44% | 60.11 | 10.57 | 8.9 | 0 | 2 | 8.9 | 6,307 | 3.43 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 354.9 | 744.9 | 1.10 | 1.13 | 0 | 1 |
| Quillota | 0.07% | 8.24% | 54,254 | 9,829 | 9.44% | 56.10 | 10.57 | 9.7 | 309 | 10 | 3.9 | 22,266 | 3.41 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,500.9 | 1,338.1 | -0.11 | 0.58 | 1 | 0 |
| Concón | 0.07% | 8.24% | 35,591 | 7,969 | 9.44% | 59.14 | 10.57 | 11.1 | 510 | 3 | 2.2 | 11,576 | 2.79 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 934.0 | 930.4 | 0.00 | 0.95 | 1 | 0 |

| | | | | | | | | | | | | | | | Climate (23) | | | | Geography (24) | | | | | | | DISPOSAL SITE? (28) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | FI (11) | EXP (12) | CON (13) | VEH (14) | EMP (15) | %LF (16) | UR (17) | EDU (18) | PP (19) | LIB (20) | IR (21) | HOU (22) | HD | WD | MT | MR | CS | C | M | V | WAS01 (25) | WAS02 (26) | %VW | PCWG02 (27) | Y | N |
| Limache | 0.07% | 8.24% | 26,490 | 5,112 | 9.44% | 54.40 | 10.57 | 9.3 | 0 | 4 | 4.1 | 11,992 | 3.27 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 218.5 | 675.4 | 2.09 | 0.57 | 1 | 0 |
| Olmué | 0.07% | 8.24% | 9,018 | 3,569 | 9.44% | 49.84 | 10.57 | 8.5 | 0 | 1 | 5.6 | 5,963 | 2.37 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 78.6 | 236.4 | 2.01 | 0.55 | 0 | 1 |
| Viña del Mar | 0.07% | 8.24% | 403,743 | 45,024 | 9.44% | 55.92 | 10.57 | 11.2 | 2,118 | 51 | 1.7 | 111,102 | 2.58 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 8,304.0 | 8,281.6 | 0.00 | 0.95 | 0 | 1 |
| Quilpué | 0.07% | 8.24% | 89,836 | 11,933 | 9.44% | 52.40 | 10.57 | 11.3 | 0 | 6 | 1.5 | 39,971 | 3.22 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 894.1 | 3,751.9 | 3.20 | 0.96 | 1 | 0 |
| Villa Alemana | 0.07% | 8.24% | 44,490 | 5,797 | 9.44% | 54.92 | 10.57 | 11.1 | 0 | 3 | 1.8 | 31,024 | 3.08 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,837.2 | 1,135.0 | -0.38 | 0.39 | 1 | 0 |
| Valparaiso | 0.07% | 8.24% | 126,741 | 36,388 | 9.44% | 61.32 | 10.57 | 10.2 | 3,192 | 60 | 1.9 | 82,216 | 3.36 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 11,160.0 | 7,540.0 | -0.32 | 0.90 | 1 | 0 |
| Casablanca | 0.07% | 8.24% | 22,789 | 2,772 | 9.44% | 59.49 | 10.57 | 8.8 | 0 | 1 | 6.2 | 7,487 | 2.92 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 310.0 | 609.0 | 0.96 | 0.92 | 1 | 0 |
| Algarrobo | 0.07% | 8.24% | 57,983 | 6,376 | 9.44% | 49.91 | 10.57 | 8.7 | 0 | 0 | 8.0 | 10,802 | 0.80 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 162.4 | 341.0 | 1.10 | 1.30 | 0 | 1 |
| El Quisco | 0.07% | 8.24% | 44,512 | 3,572 | 9.44% | 48.55 | 10.57 | 8.3 | 0 | 1 | 1.0 | 12,680 | 0.75 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 178.7 | 1,134.2 | 5.35 | 3.94 | 0 | 1 |
| El Tabo | 0.07% | 8.24% | 20,001 | 2,071 | 9.44% | 43.10 | 10.57 | 8.9 | 0 | 1 | 2.2 | 13,746 | 0.51 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 132.7 | 842.0 | 5.35 | 3.94 | 0 | 1 |
| Cartagena | 0.07% | 8.24% | 4,754 | 2,969 | 9.44% | 46.59 | 10.57 | 9.0 | 0 | 1 | 4.6 | 12,641 | 1.33 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 318.6 | 2,021.7 | 5.35 | 3.94 | 0 | 1 |
| San Antonio | 0.07% | 8.24% | 75,304 | 8,793 | 9.44% | 54.51 | 10.57 | 9.2 | 62 | 8 | 4.2 | 27,873 | 3.13 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1,646.5 | 3,472.1 | 1.11 | 1.31 | 1 | 0 |
| Santo Domingo | 0.07% | 8.24% | 33,817 | 9,209 | 9.44% | 48.12 | 10.57 | 8.5 | 0 | 0 | 8.6 | 4,774 | 1.55 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 248.0 | 295.8 | 0.19 | 1.31 | 0 | 1 |
| Juan Fernández | 0.07% | 8.24% | 35,591 | - | 9.44% | 54.80 | 10.57 | 9.0 | 0 | 0 | 5.5 | 287 | 2.21 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 14.4 | 17.9 | 0.25 | 0.93 | 0 | 1 |
| Isla de Pascua | 0.07% | 8.24% | 35,591 | - | 9.44% | 54.80 | 10.57 | 9.0 | 0 | 1 | 5.5 | 1,458 | 2.60 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 86.2 | 107.4 | 0.25 | 0.93 | 1 | 0 |
| Navidad | 0.03% | 7.24% | 2,241 | 761 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 3,688 | 1.47 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 50.0 | 50.0 | 0.00 | 0.30 | 1 | 0 |
| Litueche | 0.03% | 7.24% | 1,300 | 2,615 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 0 | 8.9 | 2,060 | 2.68 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 54.0 | 54.0 | 0.00 | 0.32 | 1 | 0 |
| Las Cabras | 0.03% | 7.24% | 12,778 | 4,283 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 2 | 8.9 | 7,840 | 2.58 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 375.0 | 375.0 | 0.00 | 0.61 | 1 | 0 |
| Coltauco | 0.03% | 7.24% | 10,823 | 1,804 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 4 | 8.9 | 4,968 | 3.27 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 97.0 | 252.0 | 1.60 | 0.51 | 1 | 0 |
| Doñihue | 0.03% | 7.24% | 5,484 | 2,776 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 2 | 8.9 | 4,797 | 3.53 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 340.1 | 466.1 | 0.37 | 0.91 | 0 | 1 |
| Rancagua | 0.03% | 7.24% | 250,660 | 31,685 | 5.15% | 54.80 | 4.52 | 10.4 | 1,550 | 29 | 2.1 | 60,501 | 3.54 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 4,310.0 | 5,905.4 | 0.37 | 0.91 | 0 | 1 |
| Graneros | 0.03% | 7.24% | 2,983 | 3,075 | 5.15% | 58.04 | 4.52 | 8.6 | 2 | 1 | 7.7 | 6,943 | 3.74 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 522.0 | 715.3 | 0.37 | 0.91 | 0 | 1 |
| Mostazal | 0.03% | 7.24% | 25,951 | 1,474 | 5.15% | 57.09 | 4.52 | 8.0 | 5 | 2 | 11.3 | 6,185 | 3.54 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 439.7 | 602.4 | 0.37 | 0.91 | 0 | 1 |
| La Estrella | 0.03% | 7.24% | 4,223 | 1,928 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 1,409 | 3.00 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 146.0 | 20.0 | -0.86 | 0.16 | 1 | 0 |
| Pichilemu | 0.03% | 7.24% | 20,166 | 2,069 | 5.15% | 50.41 | 4.52 | 7.8 | 42 | 1 | 12.6 | 5,744 | 2.16 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 110.0 | 110.0 | 0.00 | 0.29 | 1 | 0 |
| Marchihue | 0.03% | 7.24% | 5,140 | 1,381 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 2,278 | 3.03 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 144.0 | 55.0 | -0.62 | 0.26 | 1 | 0 |
| Paredones | 0.03% | 7.24% | 5,174 | 465 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 2,410 | 2.78 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 83.0 | 48.0 | -0.42 | 0.24 | 1 | 0 |
| Pichidegua | 0.03% | 7.24% | 11,261 | 2,236 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 0 | 8.9 | 5,333 | 3.33 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 182.0 | 182.0 | 0.00 | 0.34 | 1 | 0 |
| Peumo | 0.03% | 7.24% | 1,857 | 1,598 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 3,821 | 3.65 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 280.5 | 384.2 | 0.37 | 0.91 | 0 | 1 |
| San Vicente | 0.03% | 7.24% | 32,913 | 6,171 | 5.15% | 54.15 | 4.52 | 8.1 | 0 | 0 | 10.0 | 12,451 | 3.23 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 580.0 | 580.0 | 0.00 | 0.47 | 1 | 0 |
| Coinco | 0.03% | 7.24% | 2,274 | 901 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 1,843 | 3.46 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 128.4 | 175.9 | 0.37 | 0.91 | 0 | 1 |
| Quinta de Tilcoco | 0.03% | 7.24% | 4,849 | 1,501 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 2,976 | 3.82 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 228.8 | 313.6 | 0.37 | 0.91 | 0 | 1 |
| Olivar | 0.03% | 7.24% | 2,717 | 2,024 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 3,270 | 3.77 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 248.0 | 339.8 | 0.37 | 0.91 | 0 | 1 |
| Requinoa | 0.03% | 7.24% | 6,419 | 2,661 | 5.15% | 56.37 | 4.52 | 7.6 | 0 | 1 | 9.0 | 6,316 | 3.51 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 445.6 | 610.6 | 0.37 | 0.91 | 1 | 0 |
| Rengo | 0.03% | 7.24% | 23,267 | 5,496 | 5.15% | 56.31 | 4.52 | 8.1 | 61 | 5 | 8.5 | 14,575 | 3.49 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,022.1 | 1,400.4 | 0.37 | 0.91 | 0 | 1 |
| Malloa | 0.03% | 7.24% | 4,831 | 1,593 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 4,479 | 2.87 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 125.0 | 125.0 | 0.00 | 0.32 | 1 | 0 |
| Codegua | 0.03% | 7.24% | 2,348 | 2,418 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 3,013 | 3.58 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 217.1 | 297.5 | 0.37 | 0.91 | 0 | 1 |
| Machali | 0.03% | 7.24% | 58,099 | 8,916 | 5.15% | 57.85 | 4.52 | 9.9 | 0 | 2 | 3.1 | 8,038 | 3.56 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 575.6 | 788.8 | 0.37 | 0.91 | 0 | 1 |
| Peralillo | 0.03% | 7.24% | 3,451 | 1,163 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 1 | 8.9 | 2,544 | 3.82 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 109.0 | 43.7 | -0.60 | 0.15 | 1 | 0 |
| Pumanque | 0.03% | 7.24% | 490 | 660 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 0 | 8.9 | 1,106 | 3.11 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 40.0 | 40.0 | 0.00 | 0.38 | 1 | 0 |
| Lolol | 0.03% | 7.24% | 2,417 | 2,065 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 0 | 8.9 | 1,900 | 3.26 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 30.0 | 30.0 | 0.00 | 0.16 | 1 | 0 |
| Palmilla | 0.03% | 7.24% | 7,303 | 1,589 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 0 | 8.9 | 2,967 | 3.77 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 60.0 | 60.0 | 0.00 | 0.18 | 1 | 0 |
| Santa Cruz | 0.03% | 7.24% | 32,657 | 4,312 | 5.15% | 53.54 | 4.52 | 7.8 | 10 | 5 | 12.7 | 9,764 | 3.32 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 641.9 | 674.7 | 0.05 | 0.68 | 0 | 1 |
| Chépica | 0.03% | 7.24% | 4,407 | 1,412 | 5.15% | 46.09 | 4.52 | 6.8 | 0 | 1 | 15.6 | 3,924 | 3.53 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 274.6 | 288.7 | 0.05 | 0.68 | 0 | 1 |
| Nancagua | 0.03% | 7.24% | 12,963 | 2,912 | 5.15% | 61.86 | 4.52 | 7.7 | 0 | 1 | 7.9 | 4,499 | 3.47 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 309.8 | 325.7 | 0.05 | 0.68 | 0 | 1 |
| Placilla | 0.03% | 7.24% | 5,923 | 879 | 5.15% | 55.32 | 4.52 | 8.3 | 0 | 0 | 8.9 | 2,469 | 3.27 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 160.1 | 36.3 | -0.77 | 0.15 | 0 | 1 |
| Chimbarongo | 0.03% | 7.24% | 20,525 | 3,114 | 5.15% | 58.74 | 4.52 | 7.4 | 0 | 2 | 11.7 | 9,273 | 3.48 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 640.5 | 673.2 | 0.05 | 0.68 | 1 | 0 |
| San Fernando | 0.03% | 7.24% | 39,767 | 7,571 | 5.15% | 53.93 | 4.52 | 9.6 | 208 | 12 | 3.7 | 19,724 | 3.23 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,263.1 | 1,327.7 | 0.05 | 0.68 | 0 | 1 |
| Vichuquén | 0.10% | 2.81% | 5,035 | 2,734 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 0 | 10.3 | 2,734 | 1.80 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 30.0 | 54.0 | 0.80 | 0.36 | 1 | 0 |
| Licantén | 0.10% | 2.81% | 3,220 | 1,153 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 2,899 | 2.38 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 60.0 | 60.0 | 0.00 | 0.29 | 1 | 0 |
| Hualañé | 0.10% | 2.81% | 2,577 | 1,575 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 2 | 10.3 | 3,114 | 3.13 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 60.0 | 60.0 | 0.00 | 0.20 | 1 | 0 |
| Rauco | 0.10% | 2.81% | 2,257 | 1,642 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 2,669 | 3.21 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 111.0 | 235.2 | 1.12 | 0.90 | 0 | 1 |
| Sagrada Familia | 0.10% | 2.81% | 8,571 | 2,335 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 5,128 | 3.42 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 209.4 | 160.7 | -0.23 | 0.30 | 0 | 1 |
| Teno | 0.10% | 2.81% | 45,537 | 5,158 | 5.81% | 58.53 | 9.04 | 6.7 | 0 | 2 | 15.5 | 7,215 | 3.55 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 130.7 | 697.2 | 4.34 | 0.90 | 1 | 0 |
| Curicó | 0.10% | 2.81% | 103,792 | 18,481 | 5.81% | 59.34 | 9.04 | 8.9 | 0 | 11 | 7.4 | 35,034 | 3.41 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,549.8 | 3,267.6 | 1.11 | 0.90 | 0 | 1 |
| Molina | 0.10% | 2.81% | 10,230 | 4,156 | 5.81% | 51.70 | 9.04 | 8.1 | 0 | 4 | 6.1 | 11,017 | 3.50 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 499.2 | 352.8 | -0.29 | 0.30 | 1 | 0 |
| Romeral | 0.10% | 2.81% | 2,467 | 6,718 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 0 | 10.3 | 3,650 | 3.48 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 64.9 | 116.6 | 0.80 | 0.30 | 0 | 1 |
| Curepto | 0.10% | 2.81% | 3,364 | 724 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 2 | 10.3 | 3,922 | 2.76 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 51.0 | 51.0 | 0.00 | 0.16 | 1 | 0 |
| Constitución | 0.10% | 2.81% | 19,125 | 5,037 | 5.81% | 39.64 | 9.04 | 7.4 | 17 | 5 | 18.2 | 14,410 | 3.20 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 240.0 | 240.0 | 0.00 | 0.17 | 1 | 0 |
| Empedrado | 0.10% | 2.81% | 3,061 | 683 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 1,440 | 2.93 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 50.2 | 50.2 | 0.00 | 0.39 | 0 | 1 |
| Pencahue | 0.10% | 2.81% | 2,612 | 1,606 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 2,482 | 3.35 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 34.6 | 34.6 | 0.00 | 0.14 | 0 | 1 |
| San Rafael | 0.10% | 2.81% | 7,666 | 1,043 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 0 | 10.3 | 2,390 | 3.21 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 50.0 | 50.0 | 0.00 | 0.21 | 1 | 0 |
| Talca | 0.10% | 2.81% | 207,806 | 26,151 | 5.81% | 62.29 | 9.04 | 10.1 | 1,108 | 23 | 3.4 | 60,462 | 3.34 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 6,000.0 | 5,400.0 | -0.10 | 0.88 | 1 | 0 |
| Maule | 0.10% | 2.81% | 21,038 | 791 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 0 | 10.3 | 5,395 | 3.12 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 70.1 | 70.2 | 0.00 | 0.14 | 0 | 1 |
| Rio Claro | 0.10% | 2.81% | 3,935 | 1,350 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 0 | 10.3 | 3,839 | 3.31 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 62.0 | 62.0 | 0.00 | 0.16 | 1 | 0 |
| Pelarco | 0.10% | 2.81% | 264 | 824 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 0 | 10.3 | 2,239 | 3.25 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 26.0 | 26.0 | 0.00 | 0.12 | 1 | 0 |

# Table A2.1: Data per Commune

| | | | | | | | | | | | | | | | Climate (23) | | | Geography (24) | | | | | | | DISPOSAL SITE? (28) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | FI (11) | EXP (12) | CON (13) | VEH (14) | EMP (15) | %LF (16) | UR (17) | EDU (18) | PP (19) | LIB (20) | IR (21) | HOU (22) | HD | WD | MT | MR | CS | C | M | V | WAS01 (25) | WAS02 (26) | %VW | PCWG02 (27) | Y | N |
| San Clemente | 0.10% | 2.81% | 12,051 | 2,878 | 5.81% | 53.22 | 9.04 | 6.5 | 0 | 1 | 14.4 | 11,523 | 3.23 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 155.2 | 155.2 | 0.00 | 0.14 | 1 | 0 |
| Chanco | 0.10% | 2.81% | 6,076 | 1,203 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 2,825 | 3.35 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 30.0 | 330.7 | 10.02 | 1.15 | 0 | 1 |
| Pelluhue | 0.10% | 2.81% | 9,213 | 3,080 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 0 | 10.3 | 3,684 | 1.74 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 30.0 | 30.0 | 0.00 | 0.15 | 1 | 0 |
| Cauquenes | 0.10% | 2.81% | 27,785 | 3,737 | 5.81% | 44.30 | 9.04 | 7.4 | 0 | 4 | 10.8 | 13,521 | 3.05 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 489.8 | 489.8 | 0.00 | 0.39 | 1 | 0 |
| San Javier | 0.10% | 2.81% | 21,136 | 4,672 | 5.81% | 47.27 | 9.04 | 7.4 | 0 | 2 | 11.1 | 10,831 | 3.49 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 259.1 | 1,080.0 | 3.17 | 0.94 | 1 | 0 |
| Retiro | 0.10% | 2.81% | 5,461 | 960 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 5,613 | 3.29 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 242.1 | 686.5 | 1.84 | 1.22 | 1 | 0 |
| Parral | 0.10% | 2.81% | 14,734 | 5,181 | 5.81% | 53.49 | 9.04 | 8.2 | 0 | 3 | 9.6 | 11,667 | 3.24 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 420.0 | 1,325.2 | 2.16 | 1.15 | 1 | 0 |
| Villa Alegre | 0.10% | 2.81% | 7,558 | 1,189 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 0 | 10.3 | 4,405 | 3.34 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 100.9 | 420.0 | 3.16 | 0.94 | 0 | 1 |
| Linares | 0.10% | 2.81% | 89,623 | 10,806 | 5.81% | 54.37 | 9.04 | 9.1 | 210 | 7 | 6.4 | 24,922 | 3.34 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 677.5 | 2,408.7 | 2.56 | 0.95 | 1 | 0 |
| Longaví | 0.10% | 2.81% | 12,385 | 1,559 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 8,289 | 3.40 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 229.2 | 814.8 | 2.56 | 0.95 | 0 | 1 |
| Yerbas Buenas | 0.10% | 2.81% | 5,181 | 1,312 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 4,721 | 3.42 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 60.0 | 486.8 | 7.11 | 0.99 | 1 | 0 |
| Colbún | 0.10% | 2.81% | 4,065 | 1,197 | 5.81% | 52.42 | 9.04 | 8.0 | 0 | 1 | 10.3 | 5,800 | 3.04 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 143.4 | 509.8 | 2.56 | 0.95 | 0 | 1 |
| Cobquecura | 0.63% | 14.28% | 1,903 | 269 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 2,229 | 2.55 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 80.0 | 74.8 | -0.07 | 0.43 | 1 | 0 |
| Quirihue | 0.63% | 14.28% | 1,895 | 901 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 4 | 7.5 | 3,454 | 3.31 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 360.0 | 197.4 | -0.45 | 0.57 | 1 | 0 |
| Ninhue | 0.63% | 14.28% | 1,554 | 221 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 1,895 | 3.03 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 13.0 | 41.3 | 2.18 | 0.24 | 1 | 0 |
| San Carlos | 0.63% | 14.28% | 40,666 | 5,744 | 11.65% | 51.21 | 9.13 | 7.9 | 0 | 2 | 11.8 | 14,666 | 3.42 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 616.0 | 567.0 | -0.21 | 0.37 | 0 | 1 |
| Ñiquén | 0.63% | 14.28% | 3,386 | 346 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 2 | 7.5 | 3,737 | 3.06 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 20.0 | 41.3 | 1.07 | 0.12 | 1 | 0 |
| San Fabián | 0.63% | 14.28% | 6,290 | 185 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 1,259 | 2.90 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 28.0 | 28.0 | 0.00 | 0.25 | 1 | 0 |
| Trehuaco | 0.63% | 14.28% | 972 | 284 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 0 | 7.5 | 1,789 | 2.96 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 36.0 | 72.1 | 1.00 | 0.45 | 0 | 1 |
| Coelemu | 0.63% | 14.28% | 2,466 | 1,649 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 4,765 | 3.38 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 360.0 | 218.9 | -0.39 | 0.45 | 1 | 0 |
| Portezuelo | 0.63% | 14.28% | 1,218 | 402 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 0 | 7.5 | 1,752 | 3.12 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 18.0 | 43.2 | 1.40 | 0.26 | 1 | 0 |
| Ránquil | 0.63% | 14.28% | 316 | 259 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 2,043 | 2.78 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 60.0 | 47.5 | -0.21 | 0.27 | 1 | 0 |
| San Nicolás | 0.63% | 14.28% | 6,372 | 432 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 3,031 | 3.21 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 120.0 | 111.0 | -0.20 | 0.37 | 0 | 1 |
| Chillán | 0.63% | 14.28% | 125,215 | 18,903 | 11.65% | 56.38 | 9.13 | 10.1 | 1,663 | 29 | 4.3 | 46,928 | 3.45 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,982.0 | 5,104.0 | 1.78 | 1.04 | 0 | 1 |
| Chillán Viejo | 0.63% | 14.28% | 11,650 | 4,999 | 11.65% | 52.90 | 9.13 | 8.9 | 0 | 1 | 5.6 | 7,014 | 3.15 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 268.0 | 696.0 | 1.78 | 1.04 | 1 | 0 |
| Bulnes | 0.63% | 14.28% | 7,058 | 1,884 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 3 | 7.5 | 6,168 | 3.34 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 253.0 | 7,000.0 | 22.72 | 11.17 | 0 | 1 |
| Quillón | 0.63% | 14.28% | 8,705 | 1,596 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 6,225 | 2.43 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 180.0 | 248.4 | 0.38 | 0.54 | 1 | 0 |
| Pemuco | 0.63% | 14.28% | 3,485 | 421 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 0 | 7.5 | 2,571 | 3.43 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 128.0 | 92.8 | -0.28 | 0.35 | 1 | 0 |
| Coihueco | 0.63% | 14.28% | 13,432 | 1,254 | 11.65% | 50.81 | 9.13 | 6.1 | 0 | 1 | 17.7 | 6,812 | 3.46 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 100.0 | 323.1 | 2.23 | 0.45 | 1 | 0 |
| Pinto | 0.63% | 14.28% | 3,230 | 855 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 2 | 7.5 | 4,163 | 2.37 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 143.3 | 111.3 | -0.22 | 0.37 | 1 | 0 |
| San Ignacio | 0.63% | 14.28% | 8,151 | 799 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 4,962 | 3.25 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 12.0 | 12.0 | 0.00 | 0.02 | 1 | 0 |
| El Carmen | 0.63% | 14.28% | 7,895 | 809 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 0 | 7.5 | 3,956 | 3.25 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 50.0 | 113.3 | 1.27 | 0.29 | 1 | 0 |
| Yungay | 0.63% | 14.28% | 7,774 | 1,772 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 2 | 7.5 | 5,493 | 3.06 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 146.6 | 113.8 | -0.22 | 0.22 | 0 | 1 |
| Tomé | 0.63% | 14.28% | 22,500 | 2,851 | 11.65% | 46.65 | 9.13 | 9.0 | 0 | 3 | 6.6 | 15,721 | 3.34 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1,025.0 | 1,260.0 | 0.23 | 0.79 | 0 | 1 |
| Florida | 0.63% | 14.28% | 2,429 | 1,207 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 3,924 | 2.59 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 251.4 | 201.4 | -0.20 | 0.65 | 1 | 0 |
| Penco | 0.63% | 14.28% | 38,153 | 2,753 | 11.65% | 51.34 | 9.13 | 10.1 | 0 | 2 | 2.1 | 12,230 | 3.76 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1,136.7 | 1,116.0 | -0.02 | 0.80 | 1 | 0 |
| Concepción | 0.63% | 14.28% | 168,726 | 43,005 | 11.65% | 54.83 | 9.13 | 11.7 | 5,670 | 42 | 1.8 | 61,452 | 3.52 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 5,337.3 | 5,220.0 | -0.02 | 0.79 | 0 | 1 |
| Talcahuano | 0.63% | 14.28% | 207,680 | 18,761 | 11.65% | 50.13 | 9.13 | 10.3 | 0 | 10 | 2.9 | 65,040 | 3.85 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 6,789.0 | 6,048.0 | -0.11 | 0.79 | 0 | 1 |
| San Pedro de la Paz | 0.63% | 14.28% | 76,871 | 14,737 | 11.65% | 57.24 | 9.13 | 10.0 | 0 | 0 | 3.7 | 21,714 | 3.70 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1,987.2 | 1,944.0 | -0.02 | 0.79 | 0 | 1 |
| Chiguayante | 0.63% | 14.28% | 104,803 | 8,019 | 11.65% | 54.29 | 9.13 | 10.1 | 0 | 1 | 3.9 | 22,269 | 3.65 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 2,008.4 | 1,962.0 | -0.02 | 0.79 | 0 | 1 |
| Coronel | 0.63% | 14.28% | 82,207 | 5,040 | 11.65% | 45.92 | 9.13 | 9.6 | 246 | 4 | 3.0 | 26,572 | 3.60 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1,386.7 | 1,949.0 | 0.41 | 0.67 | 1 | 0 |
| Hualqui | 0.63% | 14.28% | 7,536 | 2,461 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 5,705 | 3.29 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 509.0 | 450.0 | -0.12 | 0.79 | 0 | 1 |
| Lota | 0.63% | 14.28% | 27,925 | 2,431 | 11.65% | 45.73 | 9.13 | 8.6 | 0 | 1 | 6.4 | 13,107 | 3.75 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 712.6 | 971.5 | 0.36 | 0.65 | 0 | 1 |
| Santa Juana | 0.63% | 14.28% | 4,638 | 754 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 2 | 7.5 | 4,220 | 3.01 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 184.5 | 179.7 | -0.03 | 0.46 | 1 | 0 |
| Yumbel | 0.63% | 14.28% | 6,096 | 1,690 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 2 | 7.5 | 6,674 | 3.07 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 300.0 | 138.7 | -0.54 | 0.22 | 0 | 1 |
| Cabrero | 0.63% | 14.28% | 46,077 | 2,679 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 3 | 7.5 | 7,650 | 3.30 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 220.4 | 171.1 | -0.22 | 0.22 | 1 | 0 |
| San Rosendo | 0.63% | 14.28% | 948 | 510 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 1,166 | 3.36 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 34.2 | 26.5 | -0.22 | 0.22 | 0 | 1 |
| Laja | 0.63% | 14.28% | 12,459 | 1,833 | 11.65% | 43.50 | 9.13 | 8.5 | 0 | 1 | 10.1 | 6,668 | 3.36 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 195.3 | 151.6 | -0.22 | 0.22 | 0 | 1 |
| Nacimiento | 0.63% | 14.28% | 12,897 | 2,468 | 11.65% | 45.12 | 9.13 | 7.9 | 0 | 3 | 10.6 | 7,313 | 3.55 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 317.2 | 378.7 | 0.19 | 0.48 | 1 | 0 |
| Los Angeles | 0.63% | 14.28% | 59,277 | 22,343 | 11.65% | 55.13 | 9.13 | 9.1 | 248 | 27 | 6.3 | 45,454 | 3.66 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,673.5 | 1,126.9 | -0.33 | 0.22 | 0 | 1 |
| Quilleco | 0.63% | 14.28% | 5,963 | 543 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 3,403 | 3.06 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 33.0 | 147.6 | 3.47 | 0.47 | 1 | 0 |
| Tucapel | 0.63% | 14.28% | 10,772 | 1,062 | 11.65% | 49.44 | 9.13 | 8.8 | 1 | 3 | 7.5 | 4,198 | 3.04 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 111.4 | 86.4 | -0.22 | 0.22 | 0 | 1 |
| Antuco | 0.63% | 14.28% | 415 | 504 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 0 | 7.5 | 1,559 | 2.51 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 19.0 | 75.3 | 2.96 | 0.63 | 1 | 0 |
| Santa Bárbara | 0.63% | 14.28% | 29,866 | 1,065 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 2 | 7.5 | 5,171 | 3.86 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 180.0 | 371.6 | 1.06 | 0.61 | 1 | 0 |
| Quilaco | 0.63% | 14.28% | 4,487 | 258 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 1,429 | 2.81 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 48.0 | 64.6 | 0.35 | 0.53 | 1 | 0 |
| Mulchén | 0.63% | 14.28% | 23,627 | 2,826 | 11.65% | 43.36 | 9.13 | 7.4 | 0 | 2 | 10.2 | 8,011 | 3.62 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 38.6 | 554.7 | 13.39 | 0.63 | 1 | 0 |
| Negrete | 0.63% | 14.28% | 1,086 | 756 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 2 | 7.5 | 2,467 | 3.48 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 104.7 | 125.1 | 0.19 | 0.48 | 0 | 1 |
| Arauco | 0.63% | 14.28% | 21,621 | 2,977 | 11.65% | 49.11 | 9.13 | 8.3 | 0 | 1 | 8.7 | 9,582 | 3.64 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 506.2 | 778.4 | 0.54 | 0.73 | 0 | 1 |
| Curanilahue | 0.63% | 14.28% | 14,489 | 2,202 | 11.65% | 45.18 | 9.13 | 7.7 | 0 | 1 | 9.9 | 8,176 | 3.91 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 463.7 | 713.0 | 0.54 | 0.73 | 1 | 0 |
| Lebu | 0.63% | 14.28% | 6,575 | 1,209 | 11.65% | 44.12 | 9.13 | 7.8 | 0 | 0 | 9.7 | 6,508 | 3.85 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 363.4 | 520.7 | 0.43 | 0.68 | 1 | 0 |
| Los Alamos | 0.63% | 14.28% | 6,550 | 848 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 2 | 7.5 | 5,192 | 3.59 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 270.5 | 427.2 | 0.58 | 0.75 | 1 | 0 |
| Cañete | 0.63% | 14.28% | 9,574 | 2,558 | 11.65% | 45.88 | 9.13 | 7.0 | 0 | 2 | 14.3 | 9,058 | 3.45 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 453.9 | 419.7 | -0.08 | 0.44 | 1 | 0 |
| Contulmo | 0.63% | 14.28% | 1,786 | 410 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 1 | 7.5 | 2,015 | 2.90 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 84.7 | 78.3 | -0.08 | 0.44 | 0 | 1 |
| Tirúa | 0.63% | 14.28% | 2,243 | 290 | 11.65% | 49.44 | 9.13 | 8.8 | 0 | 2 | 7.5 | 2,842 | 3.40 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 140.3 | 129.7 | -0.08 | 0.44 | 0 | 1 |
| Angol | 0.02% | 0.19% | 12,411 | 4,924 | 5.08% | 50.23 | 5.83 | 8.7 | 0 | 8 | 7.8 | 13,843 | 3.54 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1,600.0 | 1,713.0 | 0.07 | 1.15 | 1 | 0 |
| Renaico | 0.02% | 0.19% | 13,749 | 379 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 1 | 9.7 | 2,637 | 3.46 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 49.2 | 49.1 | 0.00 | 0.18 | 0 | 1 |

# Table A2.1: Data per Commune



| | | | | | | | | | | | | | | Climate (23) | | | | Geography (24) | | | | | | | DISPOSAL SITE? (28) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | FI (11) | EXP (12) | CON (13) | VEH (14) | EMP (15) | %LF (16) | UR (17) | EDU (18) | PP (19) | LIB (20) | IR (21) | HOU (22) | HD | WD | MT | MR | CS | C | M | V | WAS01 (25) | WAS02 (26) | %VW | PCWG02 (27) | Y | N |
| Collipulli | 0.02% | 0.19% | 6,388 | 1,651 | 5.08% | 51.32 | 5.83 | 7.6 | 0 | 2 | 10.4 | 6,530 | 3.42 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 436.0 | 572.0 | 0.31 | 0.84 | 1 | 0 |
| Lonquimay | 0.02% | 0.19% | 4,306 | 571 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 1 | 9.7 | 3,590 | 2.85 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 250.0 | 251.0 | 0.00 | 0.81 | 1 | 0 |
| Purén | 0.02% | 0.19% | 2,322 | 856 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 1 | 9.7 | 3,904 | 3.30 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 196.2 | 208.0 | 0.06 | 0.53 | 1 | 0 |
| Los Sauces | 0.02% | 0.19% | 669 | 882 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 1 | 9.7 | 2,283 | 3.32 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 40.8 | 40.9 | 0.00 | 0.18 | 1 | 0 |
| Ercilla | 0.02% | 0.19% | 2,864 | 413 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 1 | 9.7 | 2,449 | 3.69 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 28.0 | 28.0 | 0.00 | 0.10 | 1 | 0 |
| Lumaco | 0.02% | 0.19% | 1,370 | 670 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 1 | 9.7 | 3,275 | 3.48 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 173.9 | 9.3 | -0.95 | 0.03 | 1 | 0 |
| Traiguén | 0.02% | 0.19% | 6,318 | 1,902 | 5.08% | 49.76 | 5.83 | 7.9 | 0 | 8 | 12.0 | 5,727 | 3.41 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 290.0 | 290.0 | 0.00 | 0.49 | 1 | 0 |
| Victoria | 0.02% | 0.19% | 13,201 | 6,177 | 5.08% | 50.42 | 5.83 | 7.6 | 0 | 6 | 9.9 | 10,705 | 3.13 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 900.0 | 1,050.0 | 0.17 | 1.03 | 1 | 0 |
| Curacautín | 0.02% | 0.19% | 16,598 | 1,562 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 3 | 9.7 | 6,145 | 2.76 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 240.0 | 344.0 | 0.43 | 0.67 | 1 | 0 |
| Carahue | 0.02% | 0.19% | 8,863 | 1,434 | 5.08% | 44.94 | 5.83 | 6.2 | 0 | 2 | 15.8 | 7,170 | 3.58 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 391.8 | 450.0 | 0.15 | 0.58 | 1 | 0 |
| Nueva Imperial | 0.02% | 0.19% | 24,920 | 3,085 | 5.08% | 45.75 | 5.83 | 6.8 | 0 | 5 | 13.5 | 11,282 | 3.55 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 400.0 | 427.0 | 0.07 | 0.35 | 1 | 0 |
| Galvarino | 0.02% | 0.19% | 1,474 | 585 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 1 | 9.7 | 3,389 | 3.72 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 192.1 | 244.6 | 0.27 | 0.64 | 0 | 1 |
| Perquenco | 0.02% | 0.19% | 1,776 | 556 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 2 | 9.7 | 2,002 | 3.22 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 9.6 | 9.6 | 0.00 | 0.05 | 1 | 0 |
| Lautaro | 0.02% | 0.19% | 22,139 | 2,599 | 5.08% | 47.40 | 5.83 | 8.1 | 0 | 4 | 10.7 | 9,317 | 3.46 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 582.0 | 1,161.0 | 0.99 | 1.18 | 1 | 0 |
| Vilcún | 0.02% | 0.19% | 38,833 | 1,223 | 5.08% | 41.62 | 5.83 | 6.9 | 0 | 2 | 10.9 | 6,939 | 3.24 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 100.0 | 100.0 | 0.00 | 0.15 | 1 | 0 |
| Melipeuco | 0.02% | 0.19% | 7,168 | 314 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 0 | 9.7 | 1,994 | 2.82 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 27.0 | 27.0 | 0.00 | 0.16 | 1 | 0 |
| Temuco | 0.02% | 0.19% | 230,255 | 32,384 | 5.08% | 54.38 | 5.83 | 11.4 | 252 | 40 | 2.9 | 67,633 | 3.63 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 5,485.5 | 5,487.6 | 0.00 | 0.74 | 1 | 0 |
| Padre Las Casas | 0.02% | 0.19% | 40,611 | 6,918 | 5.08% | 50.78 | 5.83 | 8.1 | 0 | 4 | 9.0 | 15,390 | 3.82 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1,314.5 | 1,312.4 | 0.00 | 0.73 | 0 | 1 |
| Saavedra | 0.02% | 0.19% | 18,353 | 218 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 2 | 9.7 | 4,305 | 3.26 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 52.0 | 52.0 | 0.00 | 0.12 | 1 | 0 |
| Teodoro Schmidt | 0.02% | 0.19% | 14,042 | 575 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 1 | 9.7 | 5,028 | 3.08 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 51.0 | 45.0 | -0.12 | 0.10 | 1 | 0 |
| Freire | 0.02% | 0.19% | 14,384 | 1,166 | 5.08% | 44.48 | 5.83 | 7.2 | 0 | 4 | 11.3 | 7,726 | 3.30 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 164.5 | 164.5 | 0.00 | 0.21 | 1 | 0 |
| Cunco | 0.02% | 0.19% | 5,174 | 1,192 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 3 | 9.7 | 6,663 | 2.81 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 50.0 | 50.0 | 0.00 | 0.09 | 1 | 0 |
| Toltén | 0.02% | 0.19% | 3,518 | 376 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 1 | 9.7 | 3,532 | 3.18 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 18.0 | 217.8 | 11.10 | 0.64 | 0 | 1 |
| Pitrufquén | 0.02% | 0.19% | 11,212 | 2,022 | 5.08% | 46.10 | 5.83 | 8.1 | 0 | 6 | 6.3 | 7,072 | 3.11 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 130.3 | 141.0 | 0.08 | 0.21 | 1 | 0 |
| Gorbea | 0.02% | 0.19% | 4,869 | 1,088 | 5.08% | 49.14 | 5.83 | 7.3 | 0 | 4 | 11.1 | 4,995 | 3.05 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 95.0 | 143.0 | 0.51 | 0.31 | 1 | 0 |
| Loncoche | 0.02% | 0.19% | 14,693 | 1,950 | 5.08% | 51.59 | 5.83 | 7.8 | 0 | 3 | 4.6 | 7,465 | 3.09 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 104.8 | 307.0 | 1.93 | 0.44 | 1 | 0 |
| Villarrica | 0.02% | 0.19% | 54,654 | 5,627 | 5.08% | 49.06 | 5.83 | 8.1 | 0 | 6 | 7.0 | 17,235 | 2.64 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 750.0 | 1,414.0 | 0.89 | 1.02 | 1 | 0 |
| Pucón | 0.02% | 0.19% | 42,256 | 2,333 | 5.08% | 48.70 | 5.83 | 7.8 | 0 | 3 | 9.7 | 9,842 | 2.14 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 68.1 | 788.0 | 10.57 | 1.23 | 1 | 0 |
| Curarrehue | 0.02% | 0.19% | 1,255 | 427 | 5.08% | 52.16 | 5.83 | 6.3 | 0 | 0 | 12.2 | 2,059 | 3.29 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 21.9 | 253.0 | 10.56 | 1.23 | 0 | 1 |
| Mariquina | 1.57% | 6.65% | 6,826 | 1,451 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 5,764 | 3.16 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 128.3 | 57.4 | -0.55 | 0.10 | 0 | 1 |
| Lanco | 1.57% | 6.65% | 31,935 | 1,278 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 4,648 | 3.25 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 106.3 | 104.9 | -0.55 | 0.10 | 1 | 0 |
| Panguipulli | 1.57% | 6.65% | 40,071 | 2,185 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 0 | 5.1 | 11,116 | 2.99 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 207.0 | 216.0 | 0.04 | 0.21 | 1 | 0 |
| Máfil | 1.57% | 6.65% | 3,760 | 502 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 2,168 | 3.33 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 45.0 | 60.0 | 0.33 | 0.27 | 1 | 0 |
| Valdivia | 1.57% | 6.65% | 90,536 | 15,661 | 6.76% | 55.33 | 5.34 | 10.1 | 273 | 15 | 1.7 | 39,977 | 3.52 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1,851.0 | 3,392.0 | 0.83 | 0.79 | 1 | 0 |
| Los Lagos | 1.57% | 6.65% | 9,543 | 1,250 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 2 | 5.1 | 5,999 | 3.36 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 135.0 | 96.5 | -0.29 | 0.16 | 0 | 1 |
| Futrono | 1.57% | 6.65% | 7,749 | 1,260 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 0 | 5.1 | 4,707 | 3.18 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 123.3 | 71.5 | -0.42 | 0.16 | 0 | 1 |
| Corral | 1.57% | 6.65% | 3,231 | 155 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 1,943 | 2.81 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 48.0 | 72.0 | 0.50 | 0.43 | 1 | 0 |
| Paillaco | 1.57% | 6.65% | 11,871 | 1,368 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 5,458 | 3.52 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 107.0 | 92.0 | -0.14 | 0.16 | 1 | 0 |
| La Unión | 1.57% | 6.65% | 22,062 | 3,653 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 3 | 5.1 | 11,500 | 3.43 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 384.0 | 460.8 | 0.20 | 0.38 | 1 | 0 |
| Lago Ranco | 1.57% | 6.65% | 2,234 | 856 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 3,406 | 2.96 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 40.8 | 40.8 | 0.00 | 0.13 | 1 | 0 |
| RioBueno | 1.57% | 6.65% | 21,220 | 3,050 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 2 | 5.1 | 10,945 | 2.98 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 207.0 | 384.0 | 0.86 | 0.39 | 1 | 0 |
| San Juan de la Costa | 1.57% | 6.65% | 530 | 397 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 0 | 5.1 | 4,326 | 2.04 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 125.6 | 308.0 | 1.45 | 1.15 | 0 | 1 |
| San Pablo | 1.57% | 6.65% | 1,335 | 803 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 2 | 5.1 | 3,392 | 3.00 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 144.5 | 357.3 | 1.47 | 1.16 | 0 | 1 |
| Osorno | 1.57% | 6.65% | 168,428 | 18,714 | 6.76% | 53.81 | 5.34 | 9.1 | 235 | 20 | 7.0 | 43,613 | 3.34 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 2,068.3 | 5,094.3 | 1.46 | 1.15 | 1 | 0 |
| Puyehue | 1.57% | 6.65% | 6,280 | 2,817 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 3,802 | 2.99 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 161.6 | 400.4 | 1.48 | 1.16 | 0 | 1 |
| Río Negro | 1.57% | 6.65% | 2,949 | 1,050 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 2 | 5.1 | 4,934 | 2.99 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 42.0 | 90.0 | 1.14 | 0.20 | 1 | 0 |
| Purranque | 1.57% | 6.65% | 9,959 | 1,721 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 2 | 5.1 | 6,629 | 3.12 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 230.0 | 230.0 | 0.00 | 0.37 | 1 | 0 |
| Puerto Octay | 1.57% | 6.65% | 7,326 | 953 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 3,239 | 3.16 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 91.0 | 96.0 | 0.05 | 0.31 | 1 | 0 |
| Fresia | 1.57% | 6.65% | 4,766 | 1,000 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 4,147 | 3.09 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 20.0 | 192.0 | 8.60 | 0.49 | 1 | 0 |
| Frutillar | 1.57% | 6.65% | 20,142 | 1,610 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 0 | 5.1 | 4,815 | 3.22 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 60.0 | 60.0 | 0.00 | 0.13 | 1 | 0 |
| Puerto Varas | 1.57% | 6.65% | 34,011 | 4,602 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 10,603 | 3.10 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 529.8 | 529.8 | 0.00 | 0.53 | 1 | 0 |
| Llanquihue | 1.57% | 6.65% | 4,738 | 2,497 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 2 | 5.1 | 4,563 | 3.58 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 509.8 | 510.0 | 0.00 | 1.03 | 0 | 1 |
| Los Muermos | 1.57% | 6.65% | 14,193 | 1,085 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 4,989 | 3.40 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 30.0 | 30.0 | 0.00 | 0.06 | 1 | 0 |
| Puerto Montt | 1.57% | 6.65% | 125,381 | 28,416 | 6.76% | 61.25 | 5.34 | 9.4 | 48 | 24 | 5.4 | 49,004 | 3.59 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 5,490.2 | 5,490.0 | 0.00 | 1.03 | 1 | 0 |
| Maullín | 1.57% | 6.65% | 723 | 566 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 2 | 5.1 | 5,049 | 3.09 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 30.0 | 144.0 | 3.80 | 0.30 | 1 | 0 |
| Calbuco | 1.57% | 6.65% | 3,631 | 869 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 2 | 5.1 | 8,618 | 3.61 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 240.0 | 187.5 | -0.22 | 0.20 | 1 | 0 |
| Cochamó | 1.57% | 6.65% | 6,601 | 285 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 1,716 | 2.54 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 70.2 | 70.2 | 0.00 | 0.53 | 0 | 1 |
| Ancud | 1.57% | 6.65% | 11,673 | 3,920 | 6.76% | 58.51 | 5.34 | 8.0 | 0 | 4 | 6.2 | 12,404 | 3.22 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 500.0 | 325.0 | -0.35 | 0.27 | 1 | 0 |
| Dalcahue | 1.57% | 6.65% | 2,732 | 737 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 0 | 5.1 | 3,350 | 3.19 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 30.0 | 396.0 | 12.20 | 1.22 | 1 | 0 |
| Quemchi | 1.57% | 6.65% | 1,645 | 204 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 2 | 5.1 | 2,752 | 3.16 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 16.0 | 35.0 | 1.19 | 0.13 | 1 | 0 |
| Castro | 1.57% | 6.65% | 38,575 | 4,778 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 6 | 5.1 | 11,045 | 3.56 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 500.0 | 540.0 | 0.08 | 0.45 | 1 | 0 |
| Quinchao | 1.57% | 6.65% | 8,140 | 430 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 2,544 | 3.53 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 80.0 | 240.0 | 2.00 | 0.88 | 0 | 1 |
| Curaco De Vélez | 1.57% | 6.65% | 2,329 | 195 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 0 | 5.1 | 999 | 3.41 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 16.0 | 540.0 | 32.75 | 5.22 | 1 | 0 |
| Chonchi | 1.57% | 6.65% | 7,189 | 890 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 3,968 | 3.17 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 72.0 | 42.0 | -0.42 | 0.11 | 1 | 0 |
| Puqueldón | 1.57% | 6.65% | 848 | 191 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 1,287 | 3.23 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 16.0 | 38.4 | 1.40 | 0.30 | 1 | 0 |
| Queilén | 1.57% | 6.65% | 218 | 189 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 0 | 5.1 | 1,662 | 3.09 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 30.0 | 151.2 | 4.04 | 0.97 | 1 | 0 |

# Table A2.1: Data per Commune

| | | | | | | | | | | | | | | Climate (23) | | | | Geography (24) | | | | | | | DISPOSAL SITE? (28) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Commune | FI (11) | EXP (12) | CON (13) | VEH (14) | EMP (15) | %LF (16) | UR (17) | EDU (18) | PP (19) | LIB (20) | IR (21) | HOU (22) | HD | WD | MT | MR | CS | C | M | V | WAS01 (25) | WAS02 (26) | %VW | PCWG02 (27) | Y | N |
| Quellón | 1.57% | 6.65% | 10,243 | 1,101 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 6,087 | 3.59 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 300.0 | 600.0 | 1.00 | 0.90 | 1 | 0 |
| Hualaihué | 1.57% | 6.65% | 514 | 557 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 2,555 | 3.24 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 20.0 | 158.4 | 6.92 | 0.63 | 1 | 0 |
| Chaitén | 1.57% | 6.65% | 3,893 | 383 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 2,332 | 3.08 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 20.0 | 20.0 | 0.00 | 0.09 | 1 | 0 |
| Futaleufú | 1.57% | 6.65% | 3,296 | 185 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 0 | 5.1 | 838 | 2.18 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 12.0 | 96.0 | 7.00 | 1.73 | 1 | 0 |
| Palena | 1.57% | 6.65% | 1,948 | 179 | 6.76% | 57.23 | 5.34 | 9.2 | 0 | 1 | 5.1 | 758 | 2.23 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 15.0 | 16.0 | 0.07 | 0.31 | 1 | 0 |
| Guaitecas | 0.31% | 0.69% | 6,175 | 243 | 0.70% | 58.94 | 4.56 | 8.3 | 0 | 0 | 7.2 | 461 | 3.34 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 24.9 | 27.2 | 0.09 | 0.58 | 1 | 0 |
| Cisnes | 0.31% | 0.69% | 2,133 | 1,947 | 0.70% | 58.94 | 4.56 | 8.3 | 0 | 3 | 7.2 | 2,002 | 2.87 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 92.8 | 101.4 | 0.09 | 0.58 | 1 | 0 |
| Lago Verde | 0.31% | 0.69% | 89 | 51 | 0.70% | 58.94 | 4.56 | 8.3 | 0 | 1 | 7.2 | 595 | 1.78 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 17.2 | 18.8 | 0.09 | 0.58 | 1 | 0 |
| Aisén | 0.31% | 0.69% | 25,093 | - | 0.70% | 60.55 | 4.56 | 7.8 | 0 | 6 | 7.2 | 6,603 | 3.39 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 740.0 | 700.0 | -0.05 | 1.03 | 1 | 0 |
| Coihaique | 0.31% | 0.69% | 19,594 | 9,654 | 0.70% | 57.32 | 4.56 | 8.8 | 19 | 16 | 7.2 | 13,176 | 3.80 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 740.0 | 917.0 | 0.24 | 0.60 | 1 | 0 |
| Rio Ibáñez | 0.31% | 0.69% | 816 | 161 | 0.70% | 58.94 | 4.56 | 8.3 | 0 | 3 | 7.2 | 1,286 | 1.93 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 40.1 | 43.8 | 0.09 | 0.58 | 1 | 0 |
| Chile Chico | 0.31% | 0.69% | 1,293 | 531 | 0.70% | 58.94 | 4.56 | 8.3 | 0 | 2 | 7.2 | 1,853 | 2.40 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 71.9 | 78.5 | 0.09 | 0.58 | 1 | 0 |
| Tortel | 0.31% | 0.69% | 171 | - | 0.70% | 58.94 | 4.56 | 8.3 | 0 | 1 | 7.2 | 191 | 2.65 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 8.2 | 9.0 | 0.09 | 0.58 | 1 | 0 |
| Cochrane | 0.31% | 0.69% | 208 | 202 | 0.70% | 58.94 | 4.56 | 8.3 | 0 | 1 | 7.2 | 1,193 | 2.40 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 46.4 | 50.7 | 0.09 | 0.58 | 1 | 0 |
| O'Higgins | 0.31% | 0.69% | 6,175 | - | 0.70% | 58.94 | 4.56 | 8.3 | 0 | 0 | 7.2 | 259 | 1.79 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 7.5 | 8.2 | 0.09 | 0.58 | 1 | 0 |
| Natales | 0.00% | 2.94% | 6,741 | 4,414 | 1.11% | 57.84 | 5.94 | 8.4 | 0 | 2 | 5.3 | 6,731 | 2.84 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 250.0 | 250.0 | 0.00 | 0.43 | 0 | 1 |
| Torres del Paine | 0.00% | 2.94% | 600 | 376 | 1.11% | 57.61 | 5.94 | 8.7 | 0 | 1 | 3.7 | 280 | 2.64 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 3.8 | 3.8 | 0.00 | 0.17 | 1 | 0 |
| Río Verde | 0.00% | 2.94% | 8,926 | 439 | 1.11% | 57.61 | 5.94 | 8.7 | 0 | 1 | 3.7 | 208 | 1.72 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0.45 | 0.5 | 0.00 | 0.04 | 1 | 0 |
| Laguna Blanca | 0.00% | 2.94% | 8,926 | 604 | 1.11% | 57.61 | 5.94 | 8.7 | 0 | 0 | 3.7 | 277 | 2.39 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 10.0 | 10.0 | 0.00 | 0.50 | 1 | 0 |
| San Gregorio | 0.00% | 2.94% | 199 | 166 | 1.11% | 57.61 | 5.94 | 8.7 | 105 | 0 | 3.7 | 662 | 1.75 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 30.0 | 30.0 | 0.00 | 0.85 | 1 | 0 |
| Punta Arenas | 0.00% | 2.94% | 43,521 | 28,589 | 1.11% | 54.07 | 5.94 | 9.7 | 559 | 36 | 2.2 | 38,540 | 3.10 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 9,789.0 | 9,789.0 | 0.00 | 2.69 | 1 | 0 |
| Primavera | 0.00% | 2.94% | 8,926 | 315 | 1.11% | 57.61 | 5.94 | 8.7 | 83 | 0 | 3.7 | 466 | 2.18 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 96.0 | 96.0 | 0.00 | 3.11 | 1 | 0 |
| Porvenir | 0.00% | 2.94% | 1,104 | 1,046 | 1.11% | 60.92 | 5.94 | 8.1 | 0 | 2 | 3.5 | 1,949 | 2.80 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 160.0 | 160.0 | 0.00 | 0.96 | 1 | 0 |
| Timaukel | 0.00% | 2.94% | 8,926 | 217 | 1.11% | 57.61 | 5.94 | 8.7 | 0 | 0 | 3.7 | 184 | 2.30 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 2.0 | 2.0 | 0.00 | 0.16 | 1 | 0 |
| Navarino | 0.00% | 2.94% | 1,391 | 190 | 1.11% | 57.61 | 5.94 | 8.7 | 0 | 1 | 3.7 | 658 | 3.44 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 288.0 | 288.0 | 0.00 | 4.19 | 1 | 0 |
| Antártica | 0.00% | 2.94% | 8,926 | - | 1.11% | 57.61 | 5.94 | 8.7 | 0 | 3 | 3.7 | 42 | 3.10 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 9.2 | 9.2 | 0.00 | 2.32 | 0 | 1 |
| Tiltil | 23.18% | 15.87% | 6,122 | 2,048 | 43.28% | 53.60 | 7.76 | 8.2 | 0 | 1 | 6.3 | 4,910 | 3.01 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 620.4 | 507.0 | -0.18 | 1.13 | 1 | 0 |
| Colina | 23.18% | 15.87% | 153,882 | 16,774 | 43.28% | 63.69 | 7.76 | 8.4 | 0 | 5 | 5.7 | 19,697 | 3.95 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 5,603.1 | 2,676.7 | -0.52 | 1.13 | 0 | 1 |
| Lampa | 23.18% | 15.87% | 19,826 | 4,278 | 43.28% | 56.68 | 7.76 | 8.1 | 0 | 2 | 6.6 | 10,951 | 3.67 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,691.5 | 1,384.5 | -0.18 | 1.13 | 0 | 1 |
| Curacaví | 23.18% | 15.87% | 16,221 | 3,405 | 43.28% | 55.96 | 7.76 | 8.7 | 0 | 3 | 5.4 | 7,641 | 3.18 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,021.7 | 835.9 | -0.18 | 1.13 | 0 | 1 |
| Maria Pinto | 23.18% | 15.87% | 10,017 | 2,196 | 43.28% | 53.52 | 7.76 | 7.5 | 0 | 1 | 9.3 | 3,100 | 3.34 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 10.4 | 37.2 | 2.58 | 0.12 | 0 | 1 |
| Melipilla | 23.18% | 15.87% | 47,330 | 10,968 | 43.28% | 56.11 | 7.76 | 8.1 | 0 | 17 | 8.6 | 25,782 | 3.67 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 95.2 | 340.3 | 2.58 | 0.12 | 1 | 0 |
| San Pedro | 23.18% | 15.87% | 2,111 | 1,158 | 43.28% | 54.91 | 7.76 | 6.7 | 0 | 1 | 15.8 | 2,506 | 3.01 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 7.6 | 27.2 | 2.58 | 0.12 | 0 | 1 |
| Alhué | 23.18% | 15.87% | 97,736 | 938 | 43.28% | 48.83 | 7.76 | 6.7 | 0 | 1 | 14.5 | 1,416 | 3.13 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 24.0 | 21.0 | -0.13 | 0.16 | 1 | 0 |
| Paine | 23.18% | 15.87% | 35,201 | 5,584 | 43.28% | 53.76 | 7.76 | 8.3 | 0 | 5 | 5.6 | 14,256 | 3.51 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1,720.7 | 1,554.6 | -0.10 | 1.02 | 0 | 1 |
| Buin | 23.18% | 15.87% | 37,027 | 10,194 | 43.28% | 58.53 | 7.76 | 9.0 | 0 | 5 | 4.3 | 16,967 | 3.74 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 2,181.3 | 1,971.0 | -0.10 | 1.02 | 0 | 1 |
| San Bernardo | 23.18% | 15.87% | 198,662 | 19,028 | 43.28% | 59.04 | 7.76 | 9.4 | 0 | 19 | 3.3 | 61,209 | 4.03 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 8,487.5 | 8,489.0 | 0.00 | 1.13 | 0 | 1 |
| Calera de Tango | 23.18% | 15.87% | 25,465 | 6,402 | 43.28% | 59.82 | 7.76 | 8.0 | 0 | 2 | 9.8 | 4,615 | 3.95 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 627.2 | 566.4 | -0.10 | 1.02 | 0 | 1 |
| Padre Hurtado | 23.18% | 15.87% | 20,248 | 5,656 | 43.28% | 63.48 | 7.76 | 9.1 | 0 | 4 | 4.8 | 9,347 | 4.15 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1,333.4 | 1,204.8 | -0.10 | 1.02 | 0 | 1 |
| Peñaflor | 23.18% | 15.87% | 64,168 | 7,471 | 43.28% | 56.51 | 7.76 | 9.6 | 0 | 5 | 3.7 | 20,679 | 3.22 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 2,291.4 | 2,070.6 | -0.10 | 1.02 | 0 | 1 |
| El Monte | 23.18% | 15.87% | 12,912 | 3,408 | 43.28% | 58.68 | 7.76 | 8.5 | 0 | 2 | 5.7 | 5,888 | 4.49 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 26.6 | 95.3 | 2.58 | 0.12 | 0 | 1 |
| Talagante | 23.18% | 15.87% | 31,193 | 8,430 | 43.28% | 57.14 | 7.76 | 9.2 | 0 | 16 | 5.1 | 15,902 | 3.76 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 2,117.2 | 2,057.9 | -0.03 | 1.13 | 1 | 0 |
| Isla de Maipo | 23.18% | 15.87% | 16,308 | 4,581 | 43.28% | 60.86 | 7.76 | 8.1 | 0 | 3 | 5.3 | 6,898 | 3.74 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 887.3 | 887.6 | 0.00 | 1.13 | 0 | 1 |
| San José de Maipo | 23.18% | 15.87% | 5,874 | 6,302 | 43.28% | 54.55 | 7.76 | 9.7 | 0 | 2 | 3.0 | 4,784 | 2.80 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 562.4 | 460.2 | -0.18 | 1.13 | 0 | 1 |
| Puente Alto | 23.18% | 15.87% | 429,621 | 31,328 | 43.28% | 59.54 | 7.76 | 10.3 | 7,324 | 27 | 1.5 | 141,319 | 3.49 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 16,954.0 | 15,318.6 | -0.10 | 1.02 | 0 | 1 |
| Pirque | 23.18% | 15.87% | 16,634 | 15,790 | 43.28% | 57.01 | 7.76 | 9.3 | 0 | 3 | 6.1 | 4,940 | 3.35 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 569.8 | 514.8 | -0.10 | 1.02 | 0 | 1 |
| Lo Barnechea | 23.18% | 15.87% | 213,372 | 20,126 | 43.28% | 58.80 | 7.76 | 11.3 | 0 | 13 | 2.0 | 17,659 | 4.23 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 3,142.9 | 2,571.4 | -0.18 | 1.13 | 0 | 1 |
| Vitacura | 23.18% | 15.87% | 290,153 | 49,956 | 43.28% | 59.81 | 7.76 | 14.2 | 1,367 | 19 | 0.3 | 24,248 | 3.36 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 3,426.8 | 2,804.1 | -0.18 | 1.13 | 0 | 1 |
| Las Condes | 23.18% | 15.87% | 707,858 | 75,387 | 43.28% | 58.21 | 7.76 | 14.0 | 11,305 | 47 | 0.1 | 82,511 | 3.03 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 10,507.3 | 8,596.9 | -0.18 | 1.13 | 0 | 1 |
| La Reina | 23.18% | 15.87% | 81,386 | 27,864 | 43.28% | 62.79 | 7.76 | 13.4 | 3 | 16 | 0.8 | 26,050 | 3.71 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 4,068.6 | 3,329.3 | -0.18 | 1.13 | 0 | 1 |
| Peñalolén | 23.18% | 15.87% | 149,001 | 31,871 | 43.28% | 60.85 | 7.76 | 9.9 | 0 | 6 | 3.0 | 52,339 | 4.13 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 9,084.7 | 23,650.6 | 1.60 | 3.60 | 0 | 1 |
| La Florida | 23.18% | 15.87% | 245,176 | 41,849 | 43.28% | 59.42 | 7.76 | 11.5 | 3,891 | 30 | 0.9 | 97,151 | 3.76 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 12,577.5 | 11,364.0 | -0.10 | 1.02 | 0 | 1 |
| Huechuraba | 23.18% | 15.87% | 137,532 | 12,150 | 43.28% | 58.83 | 7.76 | 9.4 | 0 | 2 | 3.1 | 16,551 | 4.48 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 3,114.4 | 2,548.0 | -0.18 | 1.13 | 0 | 1 |
| Recoleta | 23.18% | 15.87% | 49,729 | 17,964 | 43.28% | 60.97 | 7.76 | 9.8 | 0 | 23 | 1.6 | 35,655 | 4.16 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 6,232.3 | 5,098.6 | -0.18 | 1.13 | 0 | 1 |
| Providencia | 23.18% | 15.87% | 188,108 | 59,916 | 43.28% | 59.67 | 7.76 | 14.3 | 1,831 | 89 | 0.2 | 52,609 | 2.30 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 5,082.4 | 4,158.7 | -0.18 | 1.13 | 0 | 1 |
| Ñuñoa | 23.18% | 15.87% | 99,191 | 38,572 | 43.28% | 54.55 | 7.76 | 13.4 | 82 | 62 | 0.2 | 55,728 | 2.93 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 6,875.2 | 5,625.1 | -0.18 | 1.13 | 0 | 1 |
| Macul | 23.18% | 15.87% | 34,480 | 19,358 | 43.28% | 59.81 | 7.76 | 11.0 | 0 | 11 | 2.3 | 30,134 | 3.73 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 4,731.8 | 7,368.9 | 0.56 | 2.15 | 0 | 1 |
| Conchali | 23.18% | 15.87% | 74,391 | 13,556 | 43.28% | 61.78 | 7.76 | 9.8 | 0 | 6 | 1.8 | 32,427 | 4.11 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 5,603.1 | 4,583.8 | -0.18 | 1.13 | 0 | 1 |
| Independencia | 23.18% | 15.87% | 17,529 | 16,191 | 43.28% | 63.53 | 7.76 | 10.4 | 0 | 22 | 3.3 | 18,367 | 3.57 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 2,753.2 | 2,252.9 | -0.18 | 1.13 | 0 | 1 |
| Santiago | 23.18% | 15.87% | 464,488 | 84,038 | 43.28% | 63.61 | 7.76 | 11.8 | 20,058 | 174 | 0.8 | 78,936 | 2.54 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 8,442.8 | 6,908.2 | -0.18 | 1.13 | 0 | 1 |
| San Joaquín | 23.18% | 15.87% | 13,460 | 10,620 | 43.28% | 57.97 | 7.76 | 9.8 | 0 | 13 | 3.0 | 24,952 | 3.91 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 4,104.9 | 3,359.2 | -0.18 | 1.13 | 0 | 1 |
| La Granja | 23.18% | 15.87% | 10,624 | 9,645 | 43.28% | 60.12 | 7.76 | 9.5 | 0 | 7 | 2.3 | 33,155 | 4.00 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 4,558.1 | 4,118.4 | -0.10 | 1.02 | 0 | 1 |
| San Ramón | 23.18% | 15.87% | 20,179 | 13,939 | 43.28% | 59.67 | 7.76 | 9.0 | 0 | 9 | 3.7 | 23,038 | 4.12 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 3,264.3 | 2,949.6 | -0.10 | 1.02 | 0 | 1 |
| La Pintana | 23.18% | 15.87% | 44,034 | 19,705 | 43.28% | 64.26 | 7.76 | 8.7 | 0 | 4 | 3.9 | 45,082 | 4.22 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 6,538.0 | 5,907.6 | -0.10 | 1.02 | 0 | 1 |
| San Miguel | 23.18% | 15.87% | 47,320 | 25,200 | 43.28% | 56.25 | 7.76 | 11.6 | 1,056 | 28 | 1.7 | 22,685 | 3.48 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 3,316.4 | 2,713.1 | -0.18 | 1.13 | 0 | 1 |
| La Cisterna | 23.18% | 15.87% | 13,298 | 13,046 | 43.28% | 54.74 | 7.76 | 11.0 | 0 | 19 | 1.4 | 22,979 | 3.70 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 3,579.0 | 2,928.9 | -0.18 | 1.13 | 0 | 1 |

# Table A2.1: Data per Commune



| Commune | FI (11) | EXP (12) | CON (13) | VEH (14) | EMP (15) | %LF (16) | UR (17) | EDU (18) | PP (19) | LIB (20) | IR (21) | HOU (22) | HD | Climate (23) WD | MT | MR | CS | Geography (24) C | M | V | WAS01 (25) | WAS02 (26) | %VW | PCWG02 (27) | DISPOSAL SITE? (28) Y | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| El Bosque | 23.18% | 15.87% | 35,127 | 23,828 | 43.28% | 59.61 | 7.76 | 9.6 | 0 | 9 | 2.0 | 43,413 | 4.04 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 6,039.6 | 5,457.0 | -0.10 | 1.02 | 0 | 1 |
| Pedro Aguirre Cerda | 23.18% | 15.87% | 5,508 | 14,838 | 43.28% | 56.13 | 7.76 | 9.1 | 0 | 7 | 3.0 | 28,688 | 3.99 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 3,940.3 | 8,598.8 | 1.18 | 2.47 | 0 | 1 |
| Lo Espejo | 23.18% | 15.87% | 4,551 | 9,723 | 43.28% | 59.48 | 7.76 | 9.0 | 0 | 4 | 2.6 | 24,770 | 4.55 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 3,879.8 | 3,505.8 | -0.10 | 1.02 | 0 | 1 |
| Quilicura | 23.18% | 15.87% | 182,212 | 11,162 | 43.28% | 55.13 | 7.76 | 9.9 | 0 | 2 | 2.8 | 35,761 | 3.54 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 5,319.7 | 4,352.4 | -0.18 | 1.13 | 0 | 1 |
| Renca | 23.18% | 15.87% | 61,698 | 15,178 | 43.28% | 57.62 | 7.76 | 8.8 | 0 | 8 | 4.9 | 32,057 | 4.17 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 5,614.1 | 4,592.9 | -0.18 | 1.13 | 0 | 1 |
| Quinta Normal | 23.18% | 15.87% | 45,167 | 16,513 | 43.28% | 57.28 | 7.76 | 10.0 | 0 | 17 | 2.6 | 25,631 | 4.06 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 4,373.4 | 3,578.9 | -0.18 | 1.13 | 0 | 1 |
| Cerro Navia | 23.18% | 15.87% | 12,783 | 10,705 | 43.28% | 57.78 | 7.76 | 8.7 | 0 | 7 | 5.5 | 33,769 | 4.39 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 6,236.1 | 5,102.5 | -0.18 | 1.13 | 0 | 1 |
| Lo Prado | 23.18% | 15.87% | 18,684 | 12,360 | 43.28% | 64.87 | 7.76 | 9.9 | 0 | 4 | 1.3 | 26,223 | 3.98 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 4,386.2 | 3,589.3 | -0.18 | 1.13 | 0 | 1 |
| Estación Central | 23.18% | 15.87% | 18,370 | 15,780 | 43.28% | 59.46 | 7.76 | 10.0 | 0 | 21 | 1.7 | 32,357 | 4.03 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 4,485.0 | 9,787.2 | 1.18 | 2.47 | 0 | 1 |
| Cerrillos | 23.18% | 15.87% | 106,878 | 18,151 | 43.28% | 58.40 | 7.76 | 10.2 | 0 | 5 | 2.2 | 19,498 | 3.69 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 2,473.2 | 5,397.2 | 1.18 | 2.47 | 0 | 1 |
| Pudahuel | 23.18% | 15.87% | 89,261 | 8,707 | 43.28% | 65.98 | 7.76 | 9.9 | 0 | 8 | 3.8 | 49,422 | 3.96 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 8,226.7 | 6,731.4 | -0.18 | 1.13 | 0 | 1 |
| Maipú | 23.18% | 15.87% | 354,147 | 41,739 | 43.28% | 61.23 | 7.76 | 11.0 | 3,720 | 21 | 1.9 | 127,362 | 3.68 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 16,110.5 | 16,113.5 | 0.00 | 1.13 | 1 | 0 |

on 2002 (inhabitants): (INE, 2003)
n2): (INE, 2001b)
'opulation (inhabitants): (INE, 2003)
pulation (number): (INE, 2003)
ups (years of age): Instituto Nacional de Estadísticas - INE. Proyeccion de Poblacion para 1999 por Edades, segun comuna (Projection of Population for 1999 per age per commune). Santiago de Chile: INE.
'opulation (%): (INE, 1992a)
, Poor Non-indigent and Non-poor population (number): (MIDEPLAN, 1998)
(USD/month): (MIDEPLAN, 1998)
ic Activity (Trade, Mining, Agriculture-Silviculture, Manufacturing): (Banco Central de Chile, 2002b)
Domestic Product: (Banco Central de Chile, 2003)
1 Investment: (Banco Central de Chile, 2002a)
s: (MIDEPLAN, 2002)
uction (m2): (INE, 1998b)
es (number): (INE, 1999)
yment (%): (INE, 2002)
Force: (MIDEPLAN, 1998)
loyment Rate (%): (INE, 2002)
of Education: (MIDEPLAN, 1998)
Performances (number): (INE, 1998c)
r of Libraries: (INE, 1998c)
te Rate (%): (MIDEPLAN, 1998)
r of Houses: (INE, 2003)
e (Warm Desert, Mild and temperate, Temperate and rainy, Cold Esteep): (Banco Central de Chile, 2002c)
phy: Own classification
Generation 2001 (tonnes/month): (CONAMA, 2002d)
Generation 2002 (tonnes/month): (CONAMA, 2003)
pita Waste Generation (kg/person-day)
nce of Disposal Sites: (CONAMA, 2003)

# APPENDIX 3

Pair-wise Correlations Matrix

# Table A3.1: Pair-wise Correlation Matrix



| | WAS02 | WAS01 | %VW | PCWG02 | Y | N | POP | DEN | URB | %URB | MEN | %MEN | 0-14 | 15-24 | 25-44 | 45-64 | 65+ | NAT | IND | %IND | PNI | %PNI | NP | %NP | INC | Tra | Min | FI | EXP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WAS02 | 1.000 | 0.910 | 0.001 | 0.376 | -0.233 | 0.233 | **0.875** | 0.458 | **0.883** | 0.502 | **0.877** | -0.251 | **0.836** | **0.826** | **0.847** | **0.831** | **0.748** | 0.007 | 0.503 | -0.243 | 0.691 | -0.308 | **0.865** | 0.315 | 0.297 | 0.432 | 0.045 | 0.357 | 0.333 |
| WAS01 | 0.910 | 1.000 | -0.123 | 0.204 | -0.248 | 0.248 | 0.936 | 0.513 | 0.946 | 0.512 | 0.937 | -0.256 | 0.895 | 0.887 | 0.910 | 0.895 | 0.815 | 0.020 | 0.527 | -0.267 | 0.716 | -0.357 | 0.931 | 0.358 | 0.366 | 0.503 | 0.024 | 0.374 | 0.352 |
| %VW | 0.001 | -0.123 | 1.000 | 0.549 | 0.004 | -0.004 | -0.102 | -0.086 | -0.104 | -0.107 | -0.102 | -0.064 | -0.100 | -0.103 | -0.103 | -0.105 | -0.099 | 0.048 | -0.046 | 0.122 | -0.086 | 0.077 | -0.104 | -0.106 | -0.086 | -0.117 | -0.014 | -0.053 | -0.045 |
| PCWG02 | 0.376 | 0.204 | 0.549 | 1.000 | -0.209 | 0.209 | 0.152 | 0.156 | 0.164 | 0.269 | 0.152 | -0.057 | 0.138 | 0.141 | 0.148 | 0.151 | 0.146 | -0.094 | 0.052 | -0.173 | 0.107 | -0.152 | 0.158 | 0.180 | 0.136 | 0.103 | 0.124 | 0.250 | 0.211 |
| Y | -0.233 | -0.248 | 0.004 | -0.209 | 1.000 | -1.000 | -0.215 | -0.360 | -0.223 | -0.274 | -0.210 | 0.222 | -0.222 | -0.227 | -0.233 | -0.248 | -0.250 | 0.025 | -0.118 | 0.180 | -0.178 | 0.204 | -0.243 | -0.217 | -0.193 | -0.353 | 0.189 | -0.149 | -0.311 |
| N | 0.233 | 0.248 | -0.004 | 0.209 | -1.000 | 1.000 | 0.215 | 0.360 | 0.223 | 0.274 | 0.210 | -0.222 | 0.222 | 0.227 | 0.233 | 0.248 | 0.250 | -0.025 | 0.118 | -0.180 | 0.178 | -0.204 | 0.243 | 0.217 | 0.193 | 0.353 | -0.189 | 0.149 | 0.311 |
| POP | 0.875 | 0.936 | -0.102 | 0.152 | -0.215 | 0.215 | 1.000 | 0.446 | **0.997** | 0.548 | **0.999** | -0.307 | **0.976** | **0.968** | **0.980** | **0.959** | **0.864** | 0.035 | 0.653 | -0.215 | 0.836 | -0.279 | **0.982** | 0.283 | 0.312 | 0.416 | -0.009 | 0.287 | 0.301 |
| DEN | 0.458 | 0.513 | -0.086 | 0.156 | -0.360 | 0.360 | 0.446 | 1.000 | 0.468 | 0.390 | 0.440 | -0.203 | 0.438 | 0.446 | 0.466 | 0.504 | 0.546 | 0.067 | 0.297 | -0.204 | 0.387 | -0.293 | 0.503 | 0.287 | 0.233 | 0.601 | -0.074 | 0.353 | 0.363 |
| URB | 0.883 | 0.946 | -0.104 | 0.164 | -0.223 | 0.223 | **0.997** | 0.468 | 1.000 | 0.562 | **0.996** | -0.291 | **0.972** | **0.965** | **0.978** | **0.958** | **0.864** | 0.022 | 0.637 | -0.233 | 0.824 | -0.301 | **0.982** | 0.306 | 0.330 | 0.431 | 0.005 | 0.303 | 0.318 |
| %URB | 0.502 | 0.512 | -0.107 | 0.269 | -0.274 | 0.274 | 0.548 | 0.390 | 0.562 | 1.000 | 0.546 | -0.492 | 0.534 | 0.547 | 0.543 | 0.560 | 0.541 | -0.003 | 0.422 | -0.143 | 0.522 | -0.083 | 0.545 | 0.120 | 0.246 | 0.295 | 0.089 | 0.251 | 0.338 |
| MEN | 0.877 | 0.937 | -0.102 | 0.152 | -0.210 | 0.210 | **0.999** | 0.440 | **0.996** | 0.546 | 1.000 | -0.302 | **0.977** | **0.967** | **0.979** | **0.955** | **0.855** | 0.033 | 0.658 | -0.211 | 0.841 | -0.272 | **0.979** | 0.277 | 0.294 | 0.413 | -0.003 | 0.290 | 0.301 |
| %MEN | -0.251 | -0.256 | -0.064 | -0.057 | 0.222 | -0.222 | -0.307 | -0.203 | -0.291 | -0.492 | -0.302 | 1.000 | -0.298 | -0.307 | -0.301 | -0.322 | -0.338 | -0.200 | -0.266 | -0.191 | -0.299 | -0.154 | -0.305 | 0.189 | 0.002 | -0.102 | 0.129 | 0.020 | -0.160 |
| 0-14 | 0.836 | 0.895 | -0.100 | 0.138 | -0.222 | 0.222 | **0.976** | 0.438 | **0.972** | 0.534 | **0.977** | -0.298 | 1.000 | 0.989 | 0.993 | 0.963 | 0.846 | 0.045 | 0.690 | -0.186 | 0.886 | -0.225 | **0.971** | 0.234 | 0.253 | 0.382 | -0.010 | 0.261 | 0.289 |
| 15-24 | 0.826 | 0.887 | -0.103 | 0.141 | -0.227 | 0.227 | **0.968** | 0.446 | **0.965** | 0.547 | **0.967** | -0.307 | 0.989 | 1.000 | 0.995 | 0.986 | 0.898 | 0.047 | 0.654 | -0.210 | 0.859 | -0.259 | **0.976** | 0.267 | 0.306 | 0.378 | -0.010 | 0.258 | 0.285 |
| 25-44 | 0.847 | 0.910 | -0.103 | 0.148 | -0.233 | 0.233 | **0.980** | 0.466 | **0.978** | 0.543 | **0.979** | -0.301 | 0.993 | 0.995 | 1.000 | 0.984 | 0.888 | 0.036 | 0.646 | -0.219 | 0.852 | -0.271 | **0.986** | 0.280 | 0.306 | 0.402 | -0.012 | 0.273 | 0.301 |
| 45-64 | 0.831 | 0.895 | -0.105 | 0.151 | -0.248 | 0.248 | **0.959** | 0.504 | **0.958** | 0.560 | **0.955** | -0.322 | 0.963 | 0.986 | 0.984 | 1.000 | 0.948 | 0.035 | 0.600 | -0.241 | 0.815 | -0.308 | **0.983** | 0.314 | 0.368 | 0.411 | -0.016 | 0.278 | 0.308 |
| 65+ | 0.748 | 0.815 | -0.099 | 0.146 | -0.250 | 0.250 | **0.864** | 0.546 | **0.864** | 0.541 | **0.855** | -0.338 | 0.846 | 0.898 | 0.888 | 0.948 | 1.000 | 0.046 | 0.498 | -0.248 | 0.696 | -0.343 | **0.907** | 0.341 | 0.432 | 0.391 | -0.043 | 0.248 | 0.282 |
| NAT | 0.007 | 0.020 | 0.048 | -0.094 | 0.025 | -0.025 | 0.035 | 0.067 | 0.022 | -0.003 | 0.033 | -0.200 | 0.045 | 0.047 | 0.036 | 0.035 | 0.046 | 1.000 | 0.169 | 0.475 | 0.046 | 0.181 | 0.025 | -0.335 | -0.107 | 0.101 | -0.206 | -0.052 | -0.200 |
| IND | 0.503 | 0.527 | -0.046 | 0.052 | -0.118 | 0.118 | 0.653 | 0.297 | 0.637 | 0.422 | 0.658 | -0.266 | 0.690 | 0.654 | 0.646 | 0.600 | 0.498 | 0.169 | 1.000 | 0.280 | 0.825 | 0.138 | 0.602 | -0.219 | -0.068 | 0.211 | -0.048 | 0.110 | 0.166 |
| %IND | -0.243 | -0.267 | 0.122 | -0.173 | 0.180 | -0.180 | -0.215 | -0.204 | -0.233 | -0.143 | -0.211 | -0.191 | -0.186 | -0.210 | -0.219 | -0.241 | -0.248 | 0.475 | 0.280 | 1.000 | -0.027 | 0.585 | -0.258 | -0.842 | -0.485 | -0.167 | -0.045 | -0.186 | -0.132 |
| PNI | 0.691 | 0.716 | -0.086 | 0.107 | -0.178 | 0.178 | 0.836 | 0.387 | 0.824 | 0.522 | 0.841 | -0.299 | 0.886 | 0.859 | 0.852 | 0.815 | 0.696 | 0.046 | 0.825 | -0.027 | 1.000 | 0.084 | 0.805 | -0.044 | 0.020 | 0.261 | -0.026 | 0.151 | 0.215 |
| %PNI | -0.308 | -0.357 | 0.077 | -0.152 | 0.204 | -0.204 | -0.279 | -0.293 | -0.301 | -0.083 | -0.272 | -0.154 | -0.225 | -0.259 | -0.271 | -0.308 | -0.343 | 0.181 | 0.138 | 0.585 | 0.084 | 1.000 | -0.337 | -0.930 | -0.603 | -0.427 | -0.055 | -0.373 | -0.240 |
| NP | 0.865 | 0.931 | -0.104 | 0.158 | -0.243 | 0.243 | **0.982** | 0.503 | **0.982** | 0.545 | **0.979** | -0.305 | **0.971** | **0.976** | **0.986** | **0.983** | **0.907** | 0.025 | 0.602 | -0.258 | 0.805 | -0.337 | 1.000 | 0.341 | 0.353 | 0.440 | -0.011 | 0.303 | 0.316 |
| %NP | 0.315 | 0.358 | -0.106 | 0.180 | -0.217 | 0.217 | 0.283 | 0.287 | 0.306 | 0.120 | 0.277 | 0.189 | 0.234 | 0.267 | 0.280 | 0.314 | 0.341 | -0.335 | -0.219 | -0.842 | -0.044 | -0.930 | 0.341 | 1.000 | 0.621 | 0.360 | 0.057 | 0.332 | 0.220 |
| INC | 0.297 | 0.366 | -0.086 | 0.136 | -0.193 | 0.193 | 0.312 | 0.233 | 0.330 | 0.246 | 0.294 | 0.002 | 0.253 | 0.306 | 0.306 | 0.368 | 0.432 | -0.107 | -0.068 | -0.485 | 0.020 | -0.603 | 0.353 | 0.621 | 1.000 | 0.307 | -0.006 | 0.245 | 0.212 |
| Tra | 0.432 | 0.503 | -0.117 | 0.103 | -0.353 | 0.353 | 0.416 | 0.601 | 0.431 | 0.295 | 0.413 | -0.102 | 0.382 | 0.378 | 0.402 | 0.411 | 0.391 | 0.101 | 0.211 | -0.167 | 0.261 | -0.427 | 0.440 | 0.360 | 0.307 | 1.000 | -0.111 | 0.467 | 0.471 |
| Min | 0.045 | 0.024 | -0.014 | 0.124 | 0.189 | -0.189 | -0.009 | -0.074 | 0.005 | 0.089 | -0.003 | 0.129 | -0.010 | -0.010 | -0.012 | -0.016 | -0.043 | -0.206 | -0.048 | -0.045 | -0.026 | -0.055 | -0.011 | 0.057 | -0.006 | -0.111 | 1.000 | 0.530 | 0.259 |
| Agr-Sil | -0.267 | -0.295 | 0.074 | -0.217 | 0.253 | -0.253 | -0.239 | -0.279 | -0.268 | -0.351 | -0.238 | -0.068 | -0.232 | -0.230 | -0.245 | -0.257 | -0.241 | 0.198 | -0.103 | 0.180 | -0.175 | 0.239 | -0.255 | -0.240 | -0.215 | -0.444 | -0.222 | -0.365 | -0.702 |
| Man | -0.095 | -0.113 | 0.024 | 0.090 | -0.071 | 0.071 | -0.086 | -0.166 | -0.073 | 0.092 | -0.087 | 0.097 | -0.064 | -0.063 | -0.065 | -0.058 | -0.046 | -0.201 | -0.042 | -0.033 | -0.016 | 0.126 | -0.087 | -0.069 | -0.021 | -0.305 | -0.153 | -0.255 | 0.244 |
| GDP | 0.481 | 0.543 | -0.090 | 0.180 | -0.474 | 0.474 | 0.456 | 0.666 | 0.469 | 0.408 | 0.450 | -0.252 | 0.426 | 0.419 | 0.445 | 0.457 | 0.445 | 0.068 | 0.248 | -0.224 | 0.312 | -0.390 | 0.483 | 0.361 | 0.349 | 0.882 | -0.090 | 0.561 | 0.630 |
| FI | 0.357 | 0.374 | -0.053 | 0.250 | -0.149 | 0.149 | 0.287 | 0.353 | 0.303 | 0.251 | 0.290 | 0.020 | 0.261 | 0.258 | 0.273 | 0.278 | 0.248 | -0.052 | 0.110 | -0.186 | 0.151 | -0.373 | 0.303 | 0.332 | 0.245 | 0.467 | 0.530 | 1.000 | 0.712 |
| EXP | 0.333 | 0.352 | -0.045 | 0.211 | -0.311 | 0.311 | 0.301 | 0.363 | 0.318 | 0.338 | 0.301 | -0.160 | 0.289 | 0.285 | 0.301 | 0.308 | 0.282 | -0.200 | 0.166 | -0.132 | 0.215 | -0.240 | 0.316 | 0.220 | 0.212 | 0.471 | 0.259 | 0.712 | 1.000 |
| CON | 0.699 | 0.777 | -0.086 | 0.118 | -0.177 | 0.177 | 0.796 | 0.216 | 0.798 | 0.421 | 0.788 | -0.234 | 0.727 | 0.759 | 0.762 | 0.781 | 0.763 | 0.015 | 0.357 | -0.232 | 0.532 | -0.340 | 0.785 | 0.331 | 0.514 | 0.331 | 0.014 | 0.244 | 0.241 |
| VEH | 0.745 | 0.812 | -0.110 | 0.171 | -0.253 | 0.253 | **0.814** | 0.435 | **0.818** | 0.520 | **0.806** | -0.299 | **0.758** | **0.813** | **0.812** | **0.864** | **0.888** | -0.003 | 0.364 | -0.333 | 0.549 | -0.455 | **0.844** | 0.454 | 0.614 | 0.454 | 0.005 | 0.310 | 0.301 |
| EMP | 0.463 | 0.525 | -0.074 | 0.159 | -0.488 | 0.488 | 0.448 | 0.658 | 0.459 | 0.406 | 0.442 | -0.306 | 0.422 | 0.415 | 0.440 | -0.452 | 0.443 | 0.114 | 0.263 | -0.179 | 0.319 | -0.338 | 0.474 | 0.306 | 0.327 | 0.856 | -0.170 | 0.485 | 0.616 |
| %LF | 0.242 | 0.301 | -0.090 | 0.041 | -0.153 | 0.153 | 0.242 | 0.293 | 0.256 | 0.073 | 0.241 | 0.172 | 0.229 | 0.232 | 0.245 | 0.242 | 0.220 | -0.273 | 0.007 | -0.486 | 0.129 | -0.507 | 0.268 | 0.557 | 0.311 | 0.440 | -0.025 | 0.218 | .0.116 |
| UR | 0.108 | 0.094 | 0.012 | 0.123 | -0.144 | 0.144 | 0.117 | 0.048 | 0.126 | 0.259 | 0.116 | -0.155 | 0.119 | 0.117 | 0.120 | 0.132 | 0.136 | -0.298 | 0.065 | -0.010 | 0.135 | 0.050 | 0.117 | -0.029 | -0.040 | 0.077 | 0.127 | 0.143 | 0.393 |
| EDU | 0.519 | 0.568 | -0.045 | 0.218 | -0.251 | 0.251 | 0.568 | 0.384 | 0.587 | 0.527 | 0.555 | -0.241 | 0.520 | 0.564 | 0.564 | 0.614 | 0.649 | -0.106 | 0.177 | -0.491 | 0.326 | -0.494 | 0.599 | 0.551 | 0.728 | 0.277 | 0.065 | 0.296 | 0.405 |
| PP | 0.382 | 0.490 | -0.048 | 0.044 | -0.130 | 0.130 | 0.471 | 0.214 | 0.477 | 0.189 | 0.464 | -0.107 | 0.423 | 0.468 | 0.484 | 0.521 | ·0.573 | 0.012 | 0.119 | -0.161 | 0.231 | -0.243 | 0.498 | 0.235 | 0.305 | 0.210 | -0.024 | 0.126 | 0.145 |
| LIB | 0.522 | 0.613 | -0.085 | 0.103 | -0.147 | 0.147 | 0.615 | 0.365 | 0.616 | 0.383 | 0.609 | -0.213 | 0.561 | 0.634 | 0.627 | 0.700 | 0.812 | 0.026 | 0.260 | -0.235 | 0.388 | -0.364 | 0.661 | 0.348 | 0.445 | 0.304 | 0.030 | 0.222 | 0.199 |
| IR | -0.447 | -0.487 | 0.016 | -0.296 | 0.203 | -0.203 | -0.460 | -0.363 | -0.483 | -0.499 | -0.456 | 0.084 | -0.434 | -0.454 | -0.457 | -0.480 | -0.474 | 0.137 | -0.180 | 0.521 | -0.327 | 0.401 | -0.480 | -0.502 | -0.496 | -0.226 | -0.149 | -0.334 | -0.358 |
| HOU | 0.849 | 0.918 | -0.094 | 0.157 | -0.210 | 0.210 | **0.985** | 0.415 | **0.982** | 0.548 | **0.982** | -0.315 | **0.951** | **0.953** | **0.964** | **0.955** | **0.892** | 0.020 | 0.603 | -0.225 | 0.802 | -0.295 | **0.971** | 0.298 | 0.344 | 0.381 | -0.019 | 0.250 | 0.270 |
| HD | 0.312 | 0.317 | -0.026 | 0.028 | -0.237 | 0.237 | 0.354 | 0.306 | 0.336 | 0.338 | 0.358 | -0.301 | 0.370 | 0.361 | 0.354 | 0.345 | 0.284 | 0.184 | 0.387 | 0.040 | 0.416 | 0.095 | 0.344 | -0.081 | 0.042 | 0.244 | -0.026 | 0.235 | 0.270 |
| WD | 0.005 | -0.008 | -0.078 | 0.005 | 0.286 | -0.286 | -0.016 | -0.117 | -0.007 | -0.041 | -0.010 | 0.175 | -0.024 | -0.021 | -0.029 | -0.034 | -0.056 | -0.239 | -0.042 | 0.066 | -0.037 | -0.074 | -0.026 | 0.019 | -0.098 | 0.050 | 0.622 | 0.267 | 0.051 |
| MT | 0.163 | 0.176 | -0.046 | 0.067 | -0.448 | 0.448 | 0.182 | 0.250 | 0.184 | 0.278 | 0.177 | -0.339 | 0.181 | 0.177 | 0.191 | 0.202 | 0.206 | -0.280 | 0.105 | -0.144 | 0.182 | 0.035 | 0.195 | 0.042 | 0.061 | 0.230 | -0.288 | 0.025 | 0.458 |
| MR | -0.157 | -0.170 | 0.160 | -0.122 | 0.213 | -0.213 | -0.134 | -0.157 | -0.153 | -0.192 | -0.133 | -0.085 | -0.125 | -0.124 | -0.137 | -0.144 | -0.126 | 0.656 | 0.010 | 0.339 | -0.102 | 0.152 | -0.146 | -0.255 | -0.135 | -0.245 | -0.123 | -0.184 | -0.416 |
| CE | -0.072 | -0.059 | -0.072 | 0.065 | 0.155 | -0.155 | -0.122 | -0.080 | -0.105 | -0.185 | -0.121 | 0.596 | -0.121 | -0.120 | -0.116 | -0.121 | -0.128 | -0.218 | -0.172 | -0.375 | -0.146 | -0.229 | -0.113 | 0.322 | 0.242 | -0.120 | -0.060 | -0.105 | -0.294 |
| C | -0.019 | -0.019 | 0.108 | 0.087 | 0.194 | -0.194 | -0.018 | -0.165 | -0.009 | 0.059 | -0.015 | 0.065 | -0.006 | 0.001 | -0.007 | -0.008 | -0.010 | -0.075 | 0.018 | -0.018 | 0.021 | 0.079 | -0.028 | -0.044 | 0.010 | -0.253 | 0.062 | -0.127 | -0.134 |
| M | -0.144 | -0.138 | -0.021 | -0.101 | 0.101 | -0.101 | -0.149 | -0.142 | -0.148 | -0.240 | -0.147 | 0.182 | -0.150 | -0.164 | -0.157 | -0.177 | -0.197 | -0.018 | -0.147 | -0.003 | -0.165 | -0.069 | -0.158 | 0.047 | -0.001 | -0.072 | 0.041 | -0.027 | -0.106 |
| V | 0.133 | 0.129 | -0.079 | 0.004 | -0.255 | 0.255 | 0.137 | 0.262 | 0.128 | 0.142 | 0.133 | -0.206 | 0.127 | 0.132 | 0.134 | 0.151 | 0.169 | 0.081 | 0.103 | 0.019 | 0.115 | -0.015 | 0.153 | 0.001 | -0.008 | 0.285 | -0.088 | 0.135 | 0.205 |

| | CON | VEH | EMP | %LF | UR | EDU | PP | LIB | IR | HOU | HD | WD | MT | MR | CE | C | M | V |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WAS02 | 0.699 | **0.745** | 0.463 | 0.242 | 0.108 | 0.519 | 0.382 | 0.522 | -0.447 | **0.849** | 0.312 | 0.005 | 0.163 | -0.157 | -0.072 | -0.019 | -0.144 | 0.133 |
| WAS01 | 0.777 | 0.812 | 0.525 | 0.301 | 0.094 | 0.568 | 0.490 | 0.613 | -0.487 | 0.918 | 0.317 | -0.008 | 0.176 | -0.170 | -0.059 | -0.019 | -0.138 | 0.129 |
| %VW | -0.086 | -0.110 | -0.074 | -0.090 | 0.012 | -0.045 | -0.048 | -0.085 | 0.016 | -0.094 | -0.026 | -0.078 | -0.046 | 0.160 | -0.072 | 0.108 | -0.021 | -0.079 |
| PCWG02 | 0.118 | 0.171 | 0.159 | 0.041 | 0.123 | 0.218 | 0.044 | 0.103 | -0.296 | 0.157 | 0.028 | 0.005 | 0.067 | -0.122 | 0.065 | 0.087 | -0.101 | 0.004 |
| Y | -0.177 | -0.253 | -0.488 | -0.153 | -0.144 | -0.251 | -0.130 | -0.147 | 0.203 | -0.210 | -0.237 | 0.286 | -0.448 | 0.213 | 0.155 | 0.194 | 0.101 | -0.255 |
| N | 0.177 | 0.253 | 0.488 | 0.153 | 0.144 | 0.251 | 0.130 | 0.147 | -0.203 | 0.210 | 0.237 | -0.286 | 0.448 | -0.213 | -0.155 | -0.194 | -0.101 | 0.255 |
| POP | 0.796 | **0.814** | 0.448 | 0.242 | 0.117 | 0.568 | 0.471 | 0.615 | -0.460 | **0.985** | 0.354 | -0.016 | 0.182 | -0.134 | -0.122 | -0.018 | -0.149 | 0.137 |
| DEN | 0.216 | 0.435 | 0.658 | 0.293 | 0.048 | 0.384 | 0.214 | 0.365 | -0.363 | 0.415 | 0.306 | -0.117 | 0.250 | -0.157 | -0.080 | -0.165 | -0.142 | 0.262 |
| URB | 0.798 | **0.818** | 0.459 | 0.256 | 0.126 | 0.587 | 0.477 | 0.616 | -0.483 | **0.982** | 0.336 | -0.007 | 0.184 | -0.153 | -0.105 | -0.009 | -0.148 | 0.128 |
| %URB | 0.421 | 0.520 | 0.406 | 0.073 | 0.259 | 0.527 | 0.189 | 0.383 | -0.499 | 0.548 | 0.338 | -0.041 | 0.278 | -0.192 | -0.185 | 0.059 | -0.240 | 0.142 |
| MEN | 0.788 | **0.806** | 0.442 | 0.241 | 0.116 | 0.555 | 0.464 | 0.609 | -0.456 | **0.982** | 0.358 | -0.010 | 0.177 | -0.133 | -0.121 | -0.015 | -0.147 | 0.133 |
| %MEN | -0.234 | -0.299 | -0.306 | 0.172 | -0.155 | -0.241 | -0.107 | -0.213 | 0.084 | -0.315 | -0.301 | 0.175 | -0.339 | -0.085 | 0.596 | 0.065 | 0.182 | -0.206 |
| 0-14 | 0.727 | **0.758** | 0.422 | 0.229 | 0.119 | 0.520 | 0.423 | 0.561 | -0.434 | **0.951** | 0.370 | -0.024 | 0.181 | -0.125 | -0.121 | -0.006 | -0.150 | 0.127 |
| 15-24 | 0.759 | **0.813** | 0.415 | 0.232 | 0.117 | 0.564 | 0.468 | 0.634 | -0.454 | **0.953** | 0.361 | -0.021 | 0.177 | -0.124 | -0.120 | 0.001 | -0.164 | 0.132 |
| 25-44 | 0.762 | **0.812** | 0.440 | 0.245 | 0.120 | 0.564 | 0.484 | 0.627 | -0.457 | **0.964** | 0.354 | -0.029 | 0.191 | -0.137 | -0.116 | -0.007 | -0.157 | 0.134 |
| 45-64 | 0.781 | **0.864** | 0.452 | 0.242 | 0.132 | 0.614 | 0.521 | 0.700 | -0.480 | **0.955** | 0.345 | -0.034 | 0.202 | -0.144 | -0.121 | -0.008 | -0.177 | 0.151 |
| 65+ | 0.763 | **0.888** | 0.443 | 0.220 | 0.136 | 0.649 | 0.573 | 0.812 | -0.474 | **0.892** | 0.284 | -0.056 | 0.206 | -0.126 | -0.128 | -0.010 | -0.197 | 0.169 |
| NAT | 0.015 | -0.003 | 0.114 | -0.273 | -0.298 | -0.106 | 0.012 | 0.026 | 0.137 | 0.020 | 0.184 | -0.239 | -0.280 | 0.656 | -0.218 | -0.075 | -0.018 | 0.081 |
| IND | 0.357 | 0.364 | 0.263 | 0.007 | 0.065 | 0.177 | 0.119 | 0.260 | -0.180 | 0.603 | 0.387 | -0.042 | 0.105 | 0.010 | -0.172 | 0.018 | -0.147 | 0.103 |
| %IND | -0.232 | -0.333 | -0.179 | -0.486 | -0.010 | -0.491 | -0.161 | -0.235 | 0.521 | -0.225 | 0.040 | 0.066 | -0.144 | 0.339 | -0.375 | -0.018 | -0.003 | 0.019 |
| PNI | 0.532 | 0.549 | 0.319 | 0.129 | 0.135 | 0.326 | 0.231 | 0.388 | -0.327 | 0.802 | 0.416 | -0.037 | 0.182 | -0.102 | -0.146 | 0.021 | -0.165 | 0.115 |
| %PNI | -0.340 | -0.455 | -0.338 | -0.507 | 0.050 | -0.494 | -0.243 | -0.364 | 0.401 | -0.295 | 0.095 | -0.074 | 0.035 | 0.152 | -0.229 | 0.079 | -0.069 | -0.015 |
| NP | 0.785 | **0.844** | 0.474 | 0.268 | 0.117 | 0.599 | 0.498 | 0.661 | -0.480 | **0.971** | 0.344 | -0.026 | 0.195 | -0.146 | -0.113 | -0.028 | -0.158 | 0.153 |
| %NP | 0.331 | 0.454 | 0.306 | 0.557 | -0.029 | 0.551 | 0.235 | 0.348 | -0.502 | 0.298 | -0.081 | 0.019 | 0.042 | -0.255 | 0.322 | -0.044 | 0.047 | 0.001 |
| INC | 0.514 | 0.614 | 0.327 | 0.311 | -0.040 | 0.728 | 0.305 | 0.445 | -0.496 | 0.344 | 0.042 | -0.098 | 0.061 | -0.135 | 0.242 | 0.010 | -0.001 | -0.008 |
| Tra | 0.331 | 0.454 | 0.856 | 0.440 | 0.077 | 0.277 | 0.210 | 0.304 | -0.226 | 0.381 | 0.244 | 0.050 | 0.230 | -0.245 | -0.120 | -0.253 | -0.072 | 0.285 |
| Min | 0.014 | 0.005 | -0.170 | -0.025 | 0.127 | 0.065 | -0.024 | 0.030 | -0.149 | -0.019 | -0.026 | 0.622 | -0.288 | -0.123 | -0.060 | 0.062 | 0.041 | -0.088 |
| Agr-Sil | -0.193 | -0.262 | -0.478 | -0.086 | -0.658 | -0.316 | -0.124 | -0.182 | 0.330 | -0.236 | -0.019 | -0.093 | -0.401 | 0.552 | 0.003 | 0.056 | 0.023 | -0.068 |
| Man | -0.075 | -0.102 | -0.117 | -0.265 | 0.593 | 0.080 | -0.030 | -0.073 | -0.097 | -0.054 | -0.172 | -0.245 | 0.385 | -0.337 | 0.128 | 0.123 | 0.016 | -0.123 |
| GDP | 0.360 | 0.472 | 0.992 | 0.321 | 0.154 | 0.410 | 0.235 | 0.321 | -0.359 | 0.421 | 0.362 | -0.183 | 0.436 | -0.274 | -0.170 | -0.258 | -0.126 | 0.333 |
| FI | 0.244 | 0.310 | 0.485 | 0.218 | 0.143 | 0.296 | 0.126 | 0.222 | -0.334 | 0.250 | 0.235 | 0.267 | 0.025 | -0.184 | -0.105 | -0.127 | -0.027 | 0.135 |
| EXP | 0.241 | 0.301 | 0.616 | 0.116 | 0.393 | 0.405 | 0.145 | 0.199 | -0.358 | 0.270 | 0.270 | 0.051 | 0.458 | -0.416 | -0.294 | -0.134 | -0.106 | 0.205 |
| CON | 1.000 | 0.859 | 0.351 | 0.193 | 0.099 | 0.574 | 0.703 | 0.679 | -0.374 | 0.837 | 0.150 | 0.012 | 0.137 | -0.116 | -0.097 | -0.018 | -0.087 | 0.087 |
| VEH | 0.859 | 1.000 | 0.455 | 0.282 | 0.108 | 0.694 | 0.675 | 0.850 | -0.475 | **0.848** | 0.213 | 0.003 | 0.175 | -0.172 | -0.072 | -0.017 | -0.145 | 0.133 |
| EMP | 0.351 | 0.455 | 1.000 | 0.274 | 0.165 | 0.409 | 0.233 | 0.308 | -0.341 | 0.415 | 0.378 | -0.259 | 0.474 | -0.234 | -0.212 | -0.255 | -0.139 | 0.340 |
| %LF | 0.193 | 0.282 | 0.274 | 1.000 | -0.177 | 0.250 | 0.152 | 0.200 | -0.277 | 0.223 | 0.063 | 0.066 | -0.067 | -0.085 | 0.191 | -0.095 | 0.034 | 0.058 |
| UR | 0.099 | 0.108 | 0.165 | -0.177 | 1.000 | 0.090 | 0.042 | 0.064 | -0.051 | 0.141 | -0.099 | 0.167 | 0.475 | -0.530 | -0.295 | -0.035 | 0.013 | 0.020 |
| EDU | 0.574 | 0.694 | 0.409 | 0.250 | 0.090 | 1.000 | 0.367 | 0.558 | -0.842 | 0.589 | 0.216 | -0.149 | 0.176 | -0.066 | -0.040 | 0.075 | -0.191 | 0.089 |
| PP | 0.703 | 0.675 | 0.233 | 0.152 | 0.042 | 0.367 | 1.000 | 0.772 | -0.223 | 0.539 | -0.007 | -0.040 | 0.106 | -0.075 | -0.032 | -0.023 | -0.039 | 0.052 |
| LIB | 0.679 | 0.850 | 0.308 | 0.200 | 0.064 | 0.558 | 0.772 | 1.000 | -0.374 | 0.682 | 0.105 | 0.018 | 0.086 | -0.096 | -0.037 | -0.008 | -0.113 | 0.099 |
| IR | -0.374 | -0.475 | -0.341 | -0.277 | -0.051 | -0.842 | -0.223 | -0.374 | 1.000 | -0.462 | -0.170 | 0.076 | -0.017 | 0.020 | -0.104 | -0.144 | 0.171 | -0.011 |
| HOU | 0.837 | **0.848** | 0.415 | 0.223 | 0.141 | 0.589 | 0.539 | 0.682 | -0.462 | 1.000 | 0.258 | -0.016 | 0.184 | -0.135 | -0.123 | 0.005 | -0.141 | 0.110 |
| HD | 0.150 | 0.213 | 0.378 | 0.063 | -0.099 | 0.216 | -0.007 | 0.105 | -0.170 | 0.258 | 1.000 | -0.195 | 0.198 | 0.040 | -0.203 | -0.203 | -0.222 | 0.361 |
| WD | 0.012 | 0.003 | -0.259 | 0.066 | 0.167 | -0.149 | -0.040 | 0.018 | 0.076 | -0.016 | -0.195 | 1.000 | -0.464 | -0.198 | -0.097 | 0.026 | 0.132 | -0.130 |
| MT | 0.137 | 0.175 | 0.474 | -0.067 | 0.475 | 0.176 | 0.106 | 0.086 | -0.017 | 0.184 | 0.198 | -0.464 | 1.000 | -0.637 | -0.313 | -0.238 | -0.170 | 0.350 |
| MR | -0.116 | -0.172 | -0.234 | -0.085 | -0.530 | -0.066 | -0.075 | -0.096 | 0.020 | -0.135 | 0.040 | -0.198 | -0.637 | 1.000 | -0.133 | 0.179 | 0.015 | -0.171 |
| CE | -0.097 | -0.072 | -0.212 | 0.191 | -0.295 | -0.040 | -0.032 | -0.037 | -0.104 | -0.123 | -0.203 | -0.097 | -0.313 | -0.133 | 1.000 | 0.145 | 0.139 | -0.242 |
| C | -0.018 | -0.017 | -0.255 | -0.095 | -0.035 | 0.075 | -0.023 | -0.008 | -0.144 | 0.005 | -0.203 | 0.026 | -0.238 | 0.179 | 0.145 | 1.000 | -0.313 | -0.637 |
| M | -0.087 | -0.145 | -0.139 | 0.034 | 0.013 | -0.191 | -0.039 | -0.113 | 0.171 | -0.141 | -0.222 | 0.132 | -0.170 | 0.015 | 0.139 | -0.313 | 1.000 | -0.533 |
| V | 0.087 | 0.133 | 0.340 | 0.058 | 0.020 | 0.089 | 0.052 | 0.099 | -0.011 | 0.110 | 0.361 | -0.130 | 0.350 | -0.171 | -0.242 | -0.637 | -0.533 | 1.000 |

# APPENDIX 4

## Analysis of Variance of the Breusch and Pagan Test and the Two-Step Weighted Least Square Method

### Breusch and Pagan Test

Model: MODEL1
Dependent Variable: WG

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Prob>F |
|---|---|---|---|---|---|
| Model | 5 | 3.56226 | 0.71245 | 234.794 | 0.0001 |
| Error | 336 | 1.01955 | 0.00303 | | |
| C Total | 341 | 4.58181 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 0.05509 | R-square | 0.7775 |
| Dep Mean | 0.05773 | Adj R-sq | 0.7742 |
| C.V. | 95.42176 | | |

Parameter Estimates

| Variable | DF | Parameter Estimate | Standard Error | T for H0: Parameter=0 | Prob > \|T\| |
|---|---|---|---|---|---|
| INTERCEP | 1 | -0.005297 | 0.02758789 | -0.192 | 0.8479 |
| POP | 1 | 0.814134 | 0.03967624 | 20.519 | 0.0001 |
| PUP | 1 | 0.021068 | 0.01243142 | 1.695 | 0.0910 |
| EDU | 1 | -0.012185 | 0.04948936 | -0.246 | 0.8057 |
| LIB | 1 | -0.087319 | 0.05134120 | -1.701 | 0.0899 |
| IND | 1 | -0.120912 | 0.03142940 | -3.847 | 0.0001 |

Breusch and Pagan Test on Linear Function

Model: MODEL1 (POP)
Dependent Variable: û (residual)

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Prob>F |
|---|---|---|---|---|---|
| Model | 1 | 0.01220 | 0.01220 | 18.044 | 0.0001 |
| Error | 340 | 0.22980 | 0.00068 | | |
| C Total | 341 | 0.24199 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 0.02600 | R-square | 0.0504 |
| Dep Mean | 0.00298 | Adj R-sq | 0.0476 |
| C.V. | 872.06685 | | |

Parameter Estimates

| Variable | DF | Parameter Estimate | Standard Error | T for H0: Parameter=0 | Prob > \|T\| |
|---|---|---|---|---|---|
| INTERCEP | 1 | -0.000881 | 0.00167421 | -0.526 | 0.5990 |
| POP | 1 | 0.043063 | 0.01013781 | 4.248 | 0.0001 |

| OBS | LAMBDA | C_CRIT |
|---|---|---|
| 1 | 686.381 | 3.84146 |

=> Lambda > C_CRIT, then the test rejects $H_0$, thus Heteroskedasticity exists

```
Model: MODEL1 (PUP)
Dependent Variable: û (residual)

Analysis of Variance
                          Sum of         Mean
Source           DF      Squares       Square       F Value       Prob>F

Model             1      0.00410      0.00410         5.853       0.0161
Error           340      0.23790      0.00070
C Total         341      0.24199

    Root MSE       0.02645     R-square        0.0169
    Dep Mean       0.00298     Adj R-sq        0.0140
    C.V.         887.30282

Parameter Estimates
                   Parameter      Standard     T for H0:
Variable   DF       Estimate         Error   Parameter=0     Prob > |T|

INTERCEP    1      -0.002819    0.00279177        -1.010         0.3133
PUP         1       0.010662    0.00440716         2.419         0.0161

OBS      LAMBDA      C_CRIT
 1      230.669     3.84146
```

=> Lambda > C_CRIT, then the test rejects $H_0$, thus Heteroskedasticity exists

```
Model: MODEL1 (EDU)
Dependent Variable: û (residual)

Analysis of Variance
                          Sum of         Mean
Source           DF      Squares       Square       F Value       Prob>F

Model             1      0.00280      0.00280         3.986       0.0467
Error           340      0.23919      0.00070
C Total         341      0.24199

    Root MSE       0.02652     R-square        0.0116
    Dep Mean       0.00298     Adj R-sq        0.0087
    C.V.         889.70767

Parameter Estimates
                   Parameter      Standard     T for H0:
Variable   DF       Estimate         Error   Parameter=0     Prob > |T|

INTERCEP    1      -0.017229    0.01022378        -1.685         0.0929
EDU         1       0.033153    0.01660562         1.997         0.0467

OBS      LAMBDA      C_CRIT
 1      157.530     3.84146
```

=> Lambda > C_CRIT, then the test rejects $H_0$, thus Heteroskedasticity exists

Appendix 4 (cont.)

Model: MODEL1 (LIB)
Dependent Variable: û (residual)

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Prob>F |
|---|---|---|---|---|---|
| Model | 1 | 0.00132 | 0.00132 | 1.871 | 0.1723 |
| Error | 340 | 0.24067 | 0.00071 | | |
| C Total | 341 | 0.24199 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 0.02661 | R-square | 0.0055 |
| Dep Mean | 0.00298 | Adj R-sq | 0.0025 |
| C.V. | 892.45592 | | |

Parameter Estimates

| Variable | DF | Parameter Estimate | Standard Error | T for H0: Parameter=0 | Prob > \|T\| |
|---|---|---|---|---|---|
| INTERCEP | 1 | 0.002157 | 0.00155967 | 1.383 | 0.1675 |
| LIB | 1 | 0.025037 | 0.01830538 | 1.368 | 0.1723 |

| OBS | LAMBDA | C_CRIT |
|---|---|---|
| 1 | 74.2641 | 3.84146 |

=> Lambda > C_CRIT, then the test rejects $H_0$, thus Heteroskedasticity exists

Model: MODEL1 (IND)
Dependent Variable: û (residual)

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Prob>F |
|---|---|---|---|---|---|
| Model | 1 | 0.00418 | 0.00418 | 5.973 | 0.0150 |
| Error | 340 | 0.23781 | 0.00070 | | |
| C Total | 341 | 0.24199 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 0.02645 | R-square | 0.0173 |
| Dep Mean | 0.00298 | Adj R-sq | 0.0144 |
| C.V. | 887.14898 | | |

Parameter Estimates

| Variable | DF | Parameter Estimate | Standard Error | T for H0: Parameter=0 | Prob > \|T\| |
|---|---|---|---|---|---|
| INTERCEP | 1 | 0.000631 | 0.00172333 | 0.366 | 0.7145 |
| IND | 1 | 0.025475 | 0.01042339 | 2.444 | 0.0150 |

| OBS | LAMBDA | C_CRIT |
|---|---|---|
| 1 | 235.170 | 3.84146 |

=> Lambda > C_CRIT, then the test rejects $H_0$, thus Heteroskedasticity exists

∴ Heteroskedasticity exists in all the explanatory variables (as confirmed by the Figures A4.1, A4.2, A4.3, A4.4 and A4.5).

Appendix 4 (cont.)

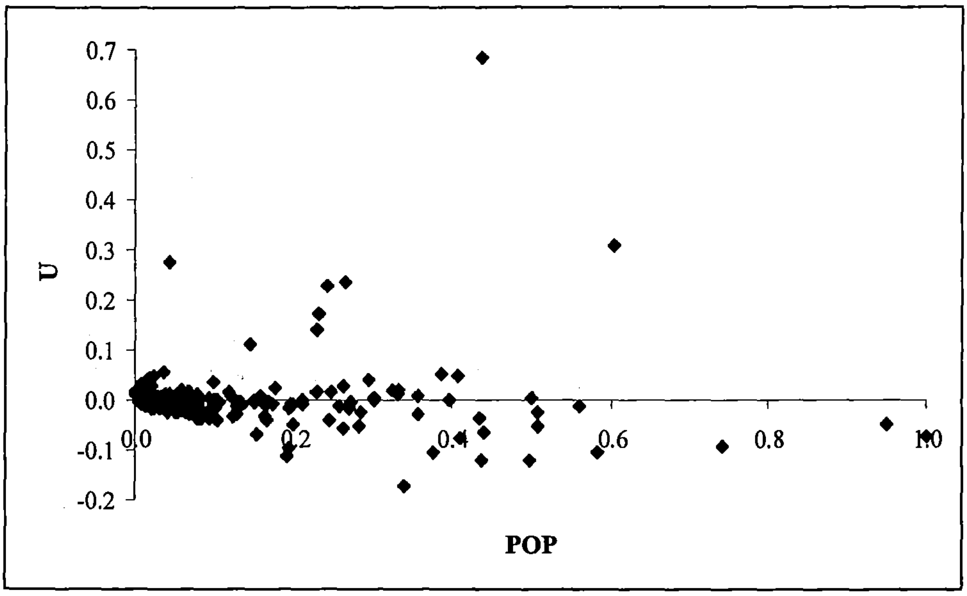



Figure A4.1: Plot of û versus POP

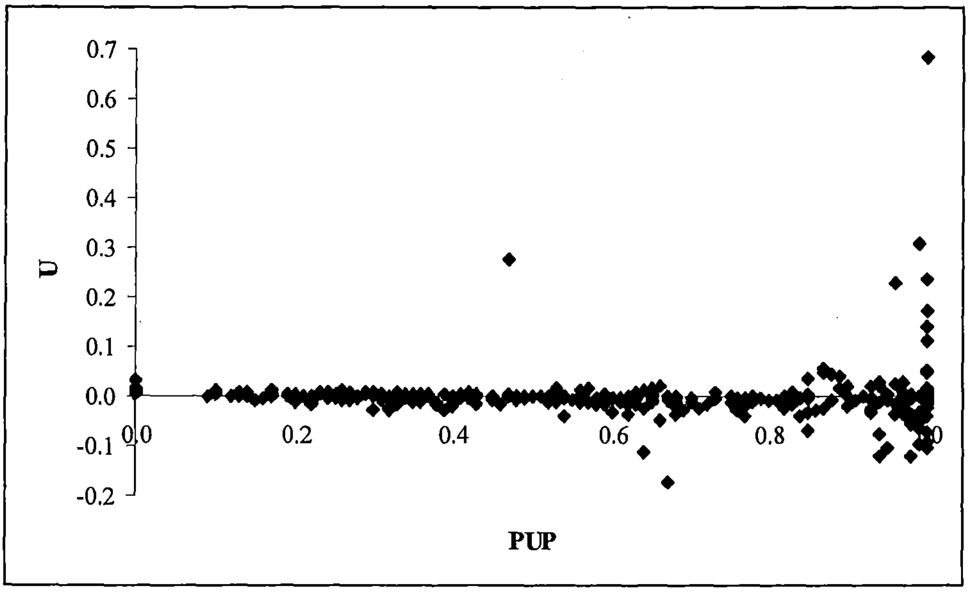



Figure A4.2: Plot of û versus PUP

Appendix 4 (cont.)

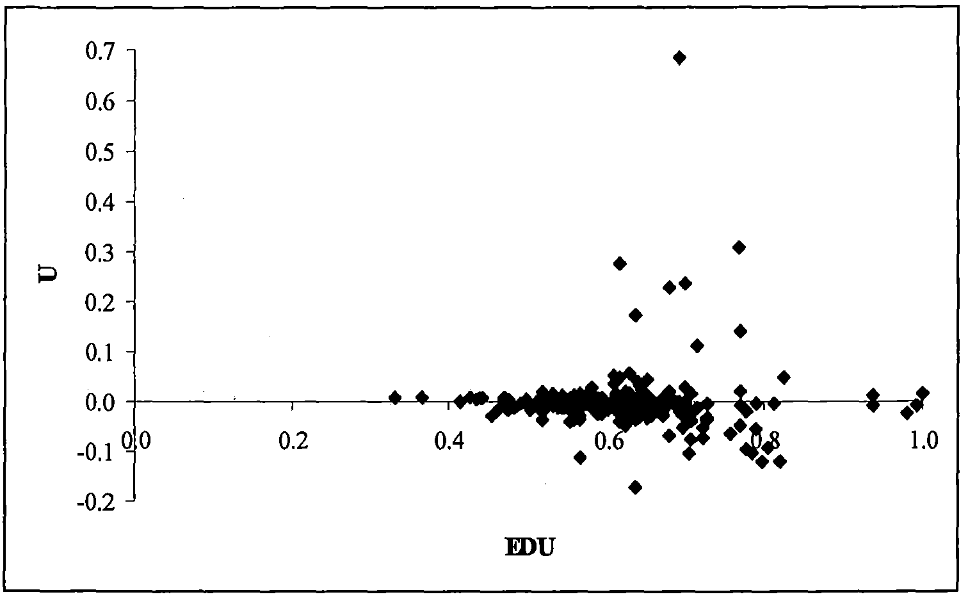



Figure A4.3: Plot of û versus EDU

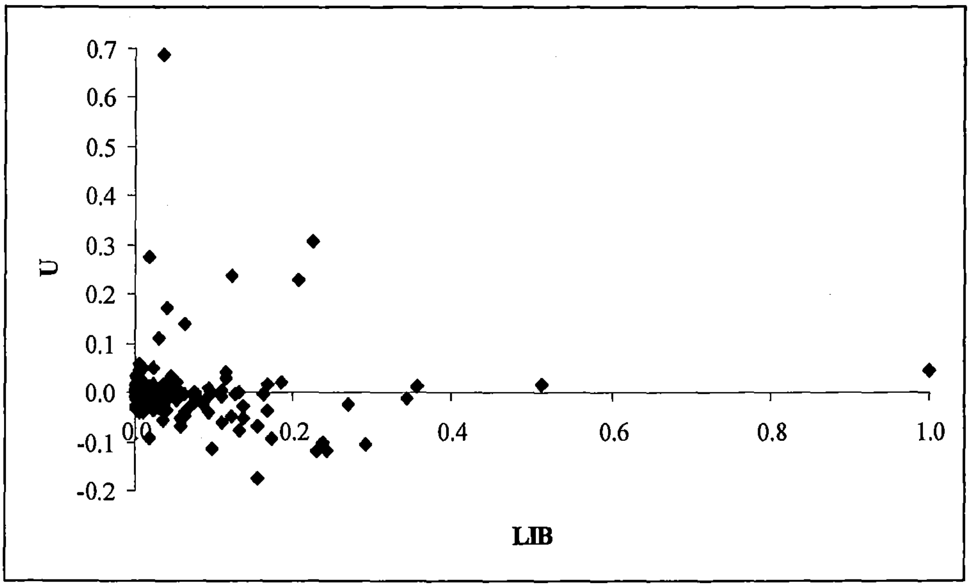



Figure A4.4: Plot of û versus LIB

Appendix 4 (cont.)

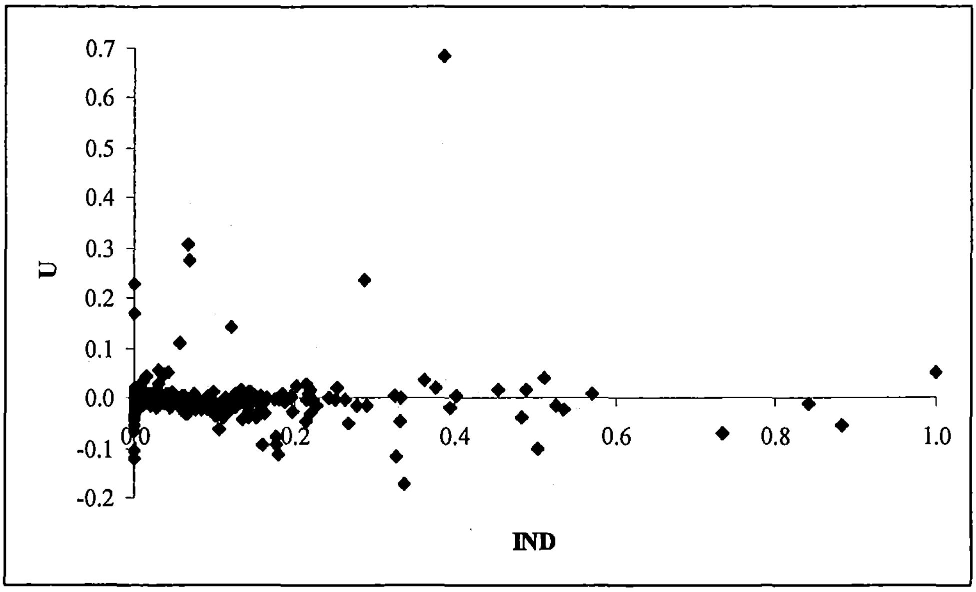



Figure A4.5: Plot of û versus IND

Weighted Least Squares Method

VARIANCE ANALYSIS AND HYPOTHESIS TEST

Model: WLS
Dependent Variable: ABSUHAT

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Prob>F |
|---|---|---|---|---|---|
| Model | 5 | 0.17250 | 0.03450 | 16.366 | 0.0001 |
| Error | 336 | 0.70829 | 0.00211 | | |
| C Total | 341 | 0.88079 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 0.04591 | R-square | 0.1958 |
| Dep Mean | 0.02014 | Adj R-sq | 0.1839 |
| C.V. | 227.93960 | | |

Parameter Estimates

| Variable | DF | Parameter Estimate | Standard Error | T for H0: Parameter=0 | Prob > \|T\| |
|---|---|---|---|---|---|
| INTERCEP | 1 | 0.014024 | 0.02299433 | 0.610 | 0.5424 |
| POP | 1 | 0.197678 | 0.03306990 | 5.978 | 0.0001 |
| PUP | 1 | 0.010223 | 0.01036151 | 0.987 | 0.3245 |
| EDU | 1 | -0.017883 | 0.04124907 | -0.434 | 0.6649 |
| LIB | 1 | -0.038882 | 0.04279257 | -0.909 | 0.3642 |
| IND | 1 | -0.054104 | 0.02619621 | -2.065 | 0.0397 |

Appendix 4 (cont.)

```
Model: MODEL1
NOTE: No intercept in model. R-square is redefined.
Dependent Variable: WGW

Analysis of Variance
                            Sum of          Mean
Source            DF       Squares        Square       F Value       Prob>F

Model              6    1689.38389     281.56398        89.380       0.0001
Error            336    1058.46449       3.15019
U Total          342    2747.84838

    Root MSE       1.77488     R-square        0.6148
    Dep Mean       1.76617     Adj R-sq        0.6079
    C.V.         100.49319

Parameter Estimates
                    Parameter       Standard     T for H0:
Variable  DF         Estimate          Error   Parameter=0    Prob > |T|

CW         1        -0.018260     0.00917240        -1.991        0.0473
POPW       1         0.646656     0.05151975        12.552        0.0001
PUPW       1         0.000037     0.00416389         0.009        0.9928
EDUW       1         0.026783     0.01539216         1.740        0.0828
LIBW       1         0.032282     0.06529686         0.494        0.6214
INDW       1        -0.042246     0.01428364        -2.958        0.0033
```

```
SAS Programme

TITLE 'VARIANCE ANALYSIS AND HYPOTHESIS TEST';
OPTIONS LINESIZE=72 NODATE NONUMBER NOCENTER;
DATA ONE;                                             *create a data set;
INFILE 'E:\Eduardo\Research\Thesis\Part1\1.1 Data Processing\Model
3\Scaled Data 2\data.prn';
INPUT WG POP PUP EDU LIB IND;                           *input variables;

PROC REG;                                        *estimate the regression;
MODEL WG = POP PUP EDU LIB IND;                       *UNRESTRICTED MODEL;
OUTPUT OUT=OUT1 R=UHAT;     * UHAT is the residuals from the regression;

DATA TWO; SET OUT1;
UHAT_SQ=UHAT**2;

DATA BP; MERGE ONE TWO;
     * Data set BP includes the original data set and squared residuals;
PROC REG DATA=BP;
MODEL UHAT_SQ = POP;

DATA TEST1;
N=342; RSS=1.01955; SIGHATSQ=RSS/N; ESS=0.01220; S0=ESS;
SIGHAT4=SIGHATSQ**2;
LAMBDA=S0/(2*SIGHAT4);
C_CRIT = CINV(.95,1);                  * Obtain ChiSquare Critical value;
PROC PRINT DATA=TEST1;
VAR LAMBDA C_CRIT;

DATA BP; MERGE ONE TWO;
     * Data set BP includes the original data set and squared residuals;
PROC REG DATA=BP;
MODEL UHAT_SQ = PUP;
```

Appendix 4 (cont.)

```
DATA TEST2;
N=342; RSS=1.01955; SIGHATSQ=RSS/N; ESS=0.00410; S0=ESS;
SIGHAT4=SIGHATSQ**2;
LAMBDA=S0/(2*SIGHAT4);
C_CRIT = CINV(.95,1);                    * obtain ChiSquare Critical value;
PROC PRINT DATA=TEST2;
VAR LAMBDA C_CRIT;

DATA BP; MERGE ONE TWO;
     * Data set BP includes the original data set and squared residuals;
PROC REG DATA=BP;
MODEL UHAT_SQ = EDU;

DATA TEST3;
N=342; RSS=1.01955; SIGHATSQ=RSS/N; ESS=0.00280; S0=ESS;
SIGHAT4=SIGHATSQ**2;
LAMBDA=S0/(2*SIGHAT4);
C_CRIT = CINV(.95,1);                    * obtain ChiSquare Critical value;
PROC PRINT DATA=TEST3;
VAR LAMBDA C_CRIT;

DATA BP; MERGE ONE TWO;
     * Data set BP includes the original data set and squared residuals;
PROC REG DATA=BP;
MODEL UHAT_SQ = LIB;

DATA TEST4;
N=342; RSS=1.01955; SIGHATSQ=RSS/N; ESS=0.00132; S0=ESS;
SIGHAT4=SIGHATSQ**2;
LAMBDA=S0/(2*SIGHAT4);
C_CRIT = CINV(.95,1);                    * obtain ChiSquare Critical value;
PROC PRINT DATA=TEST4;
VAR LAMBDA C_CRIT;

DATA BP; MERGE ONE TWO;
     * Data set BP includes the original data set and squared residuals;
PROC REG DATA=BP;
MODEL UHAT_SQ = IND;

DATA TEST5;
N=342; RSS=1.01955; SIGHATSQ=RSS/N; ESS=0.00418; S0=ESS;
SIGHAT4=SIGHATSQ**2;
LAMBDA=S0/(2*SIGHAT4);
C_CRIT = CINV(.95,1);                    * obtain ChiSquare Critical value;
PROC PRINT DATA=TEST5;
VAR LAMBDA C_CRIT;

RUN;


TITLE 'VARIANCE ANALYSIS AND HYPOTHESIS TEST';
OPTIONS LINESIZE=72 NODATE NONUMBER NOCENTER;
DATA ONE;                                                  *create a data set;
INFILE 'E:\Eduardo\Research\Thesis\Part1\1.1 Data Processing\Model
3\Scaled Data 2\data.prn';
INPUT WG POP PUP EDU LIB IND;                              *input variables;

PROC REG;                                          *estimate the regression;
MODEL WG = POP PUP EDU LIB IND;                         *UNRESTRICTED MODEL;
OUTPUT OUT=OUT1 R=UHAT;       * UHAT is the residuals from the regression;

DATA TWO; SET OUT1;
ABSUHAT=ABS(UHAT);
```

Appendix 4 (cont.)

```
PROC REG DATA=TWO;
WLS: MODEL ABSUHAT = POP PUP EDU LIB IND;

DATA WLS; SET TWO;
WG_W=0.014024+0.197678*POP+0.010223*PUP-0.017883*EDU-0.038882*LIB-
0.054104*IND;
WGW=WG/WG_W; POPW=POP/WG_W; PUPW=PUP/WG_W; EDUW=EDU/WG_W; LIBW=LIB/WG_W;
INDW=IND/WG_W; CW=1/WG_W;  *Transform the variables;

PROC REG DATA=WLS;    *Estimate the weighted least squares (WLS);

MODEL WGW = CW POPW PUPW EDUW LIBW INDW / NOINT;   *specify a model
without a constant term;

RUN;
```

Appendix 4 (cont.)

# APPENDIX 5

Multi-Layer Perceptron Neural Network Results

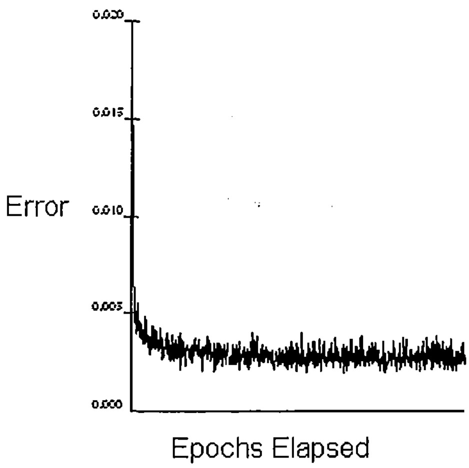



Figure A5.1: Training Set Average Error versus Epochs Elapsed

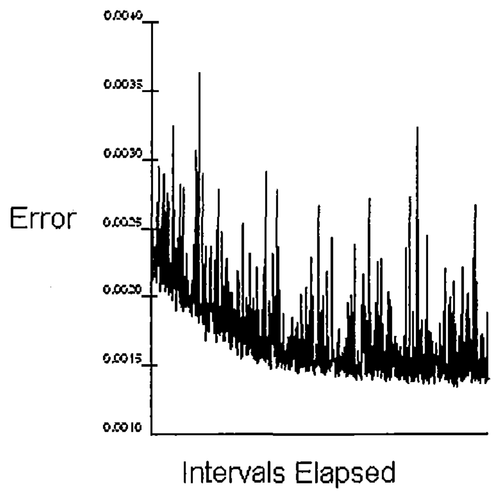
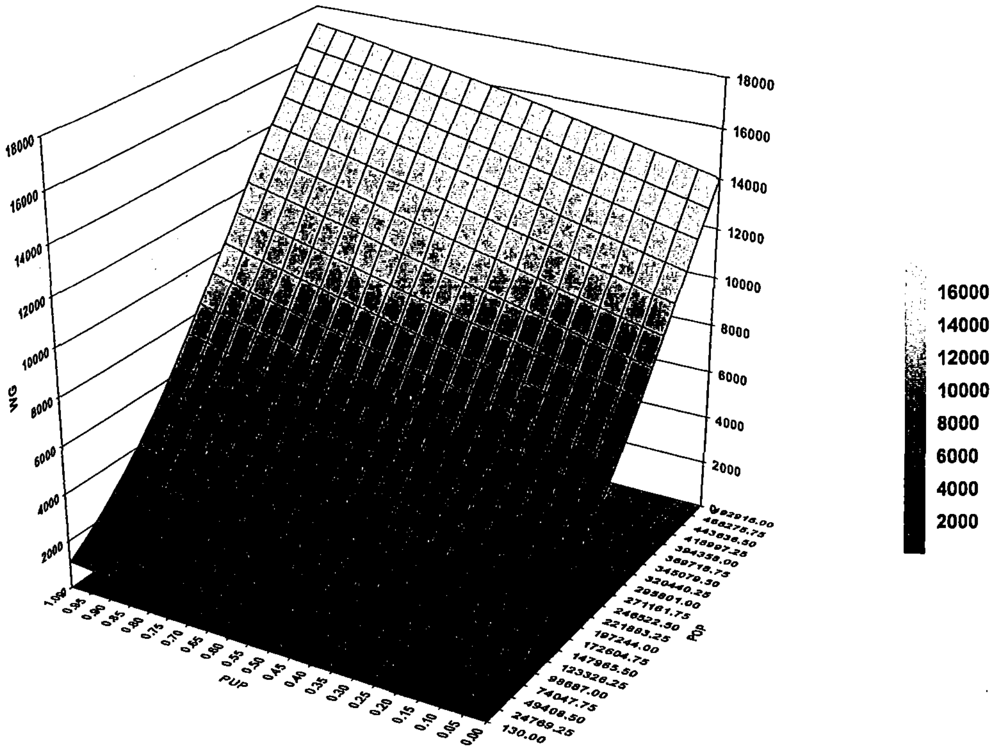
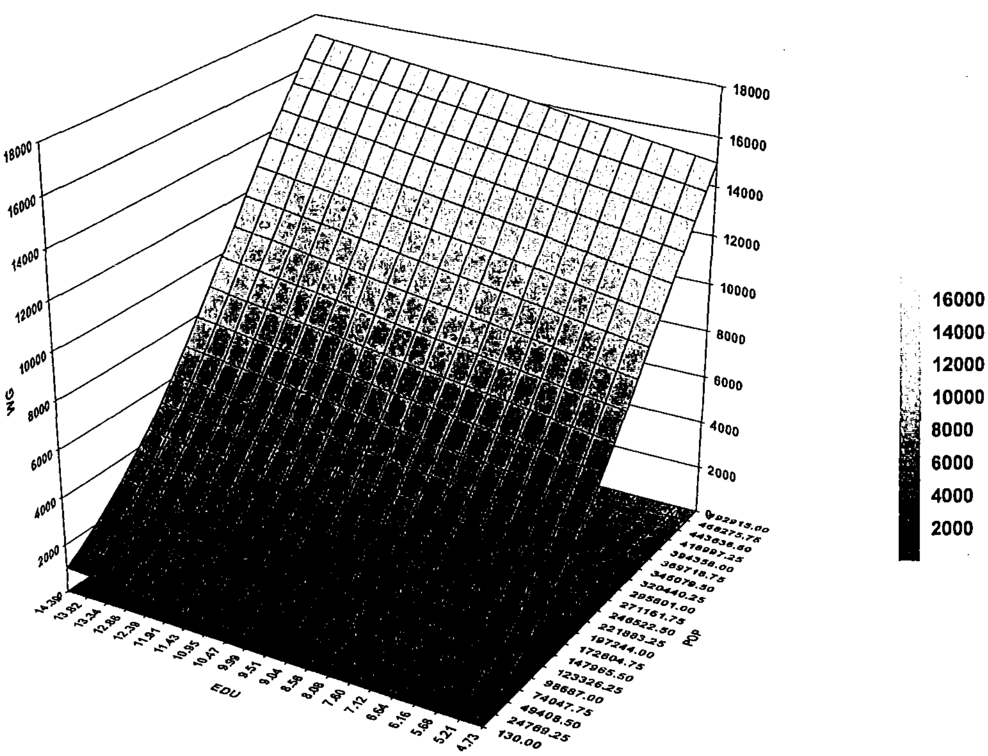


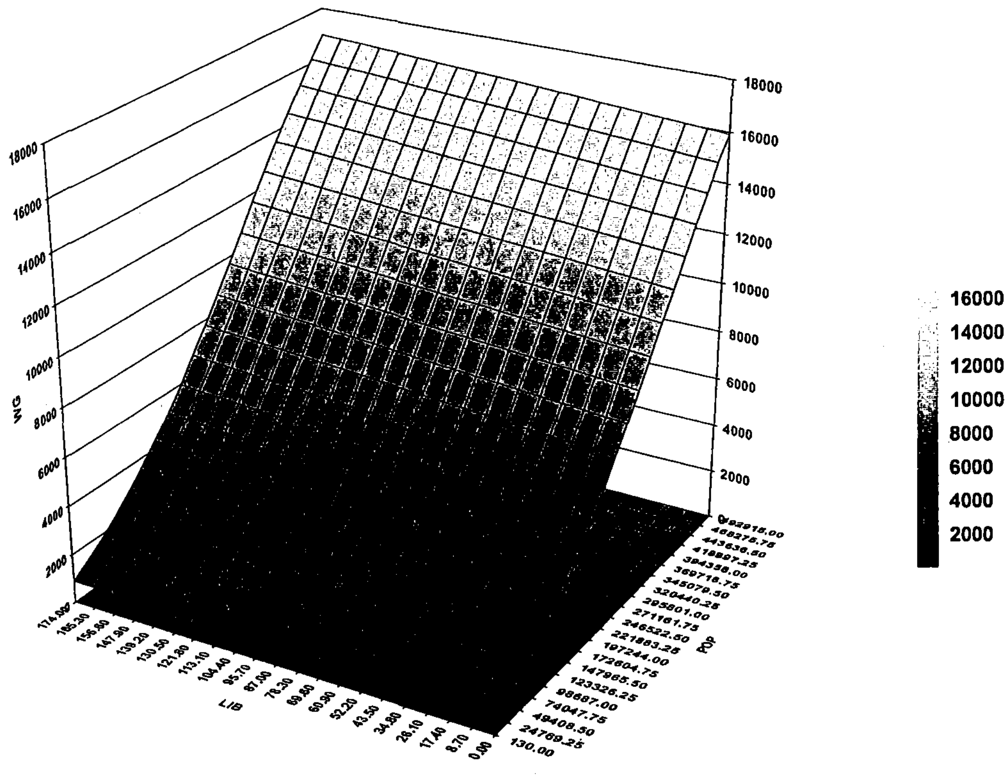

Figure A5.2: Testing Ser Average Error versus Intervals Elapsed

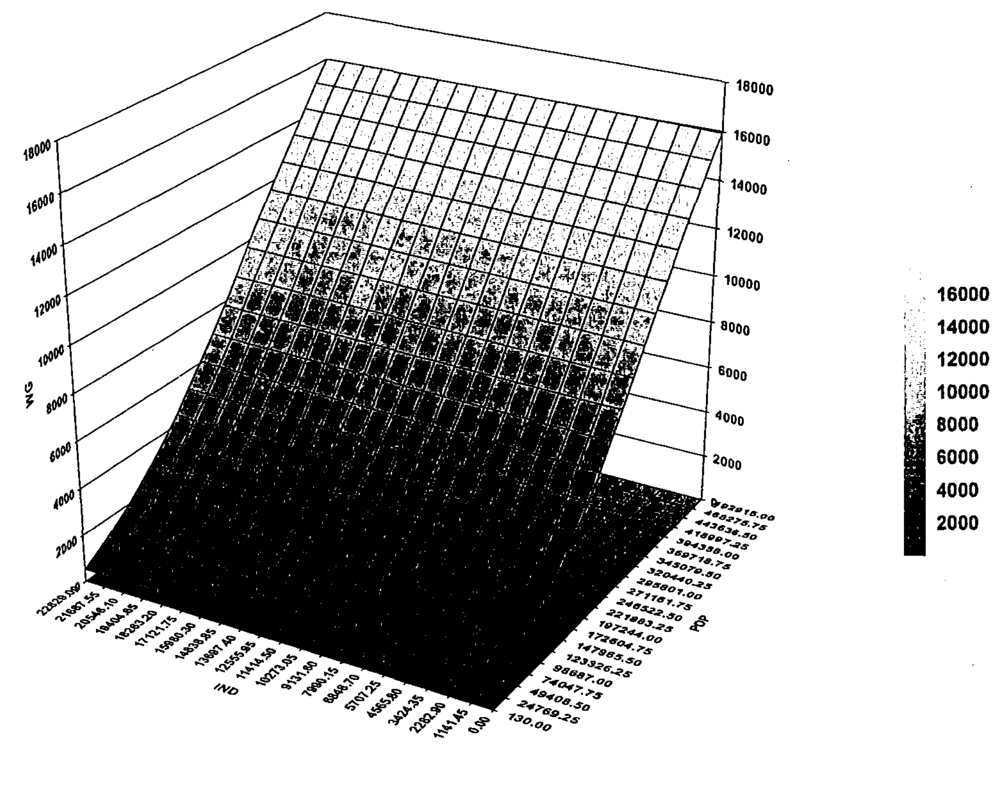
NeuroShell 2 – Release 4.0 (1993-1998) by Ward Systems Group®, Inc.
Licensed to Lincoln University.

Figure A6.1: 3D plots of the Explanatory Variables against Waste Generation

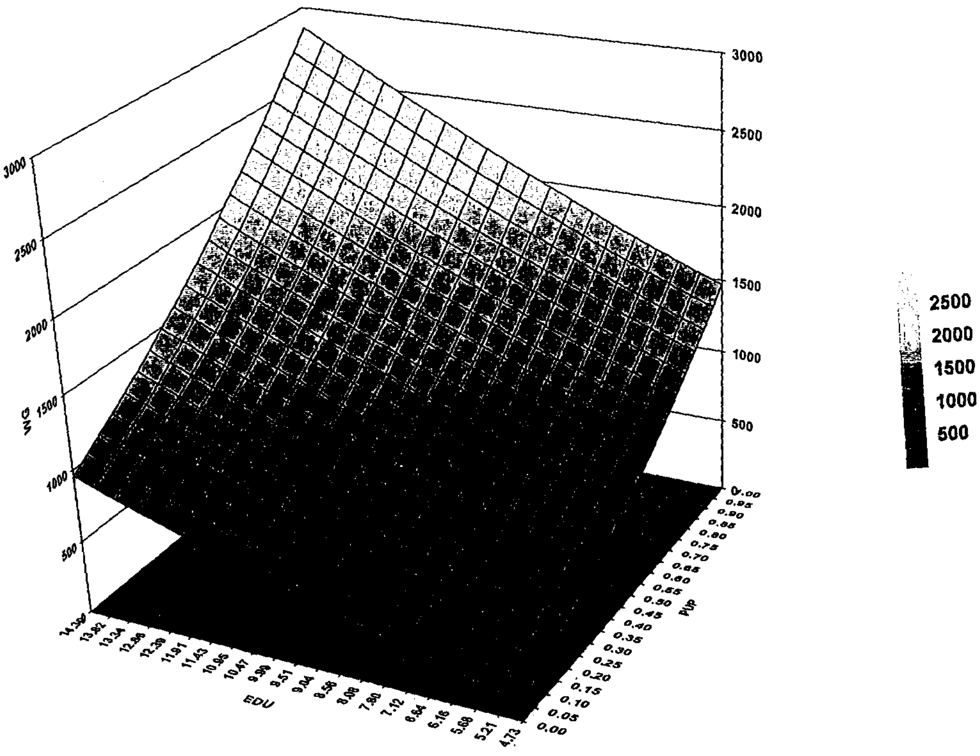


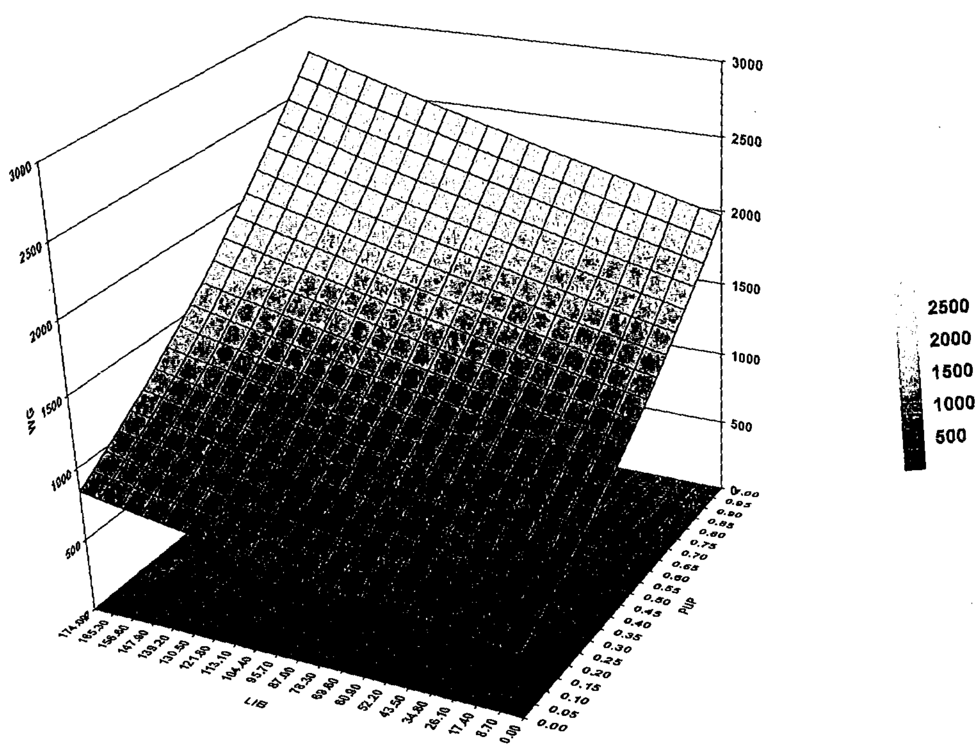





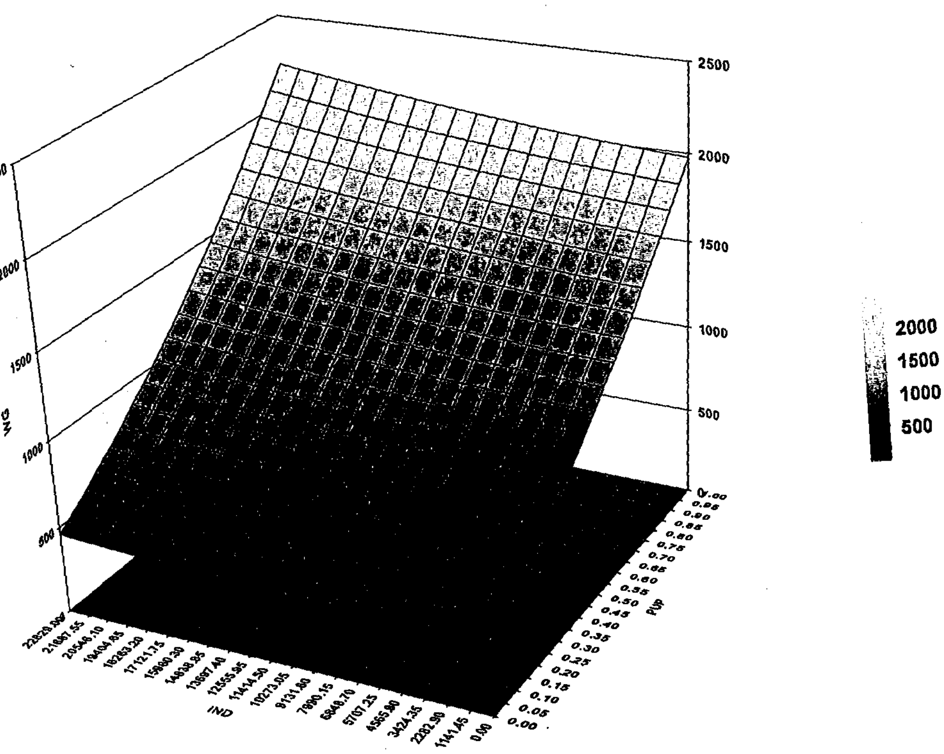



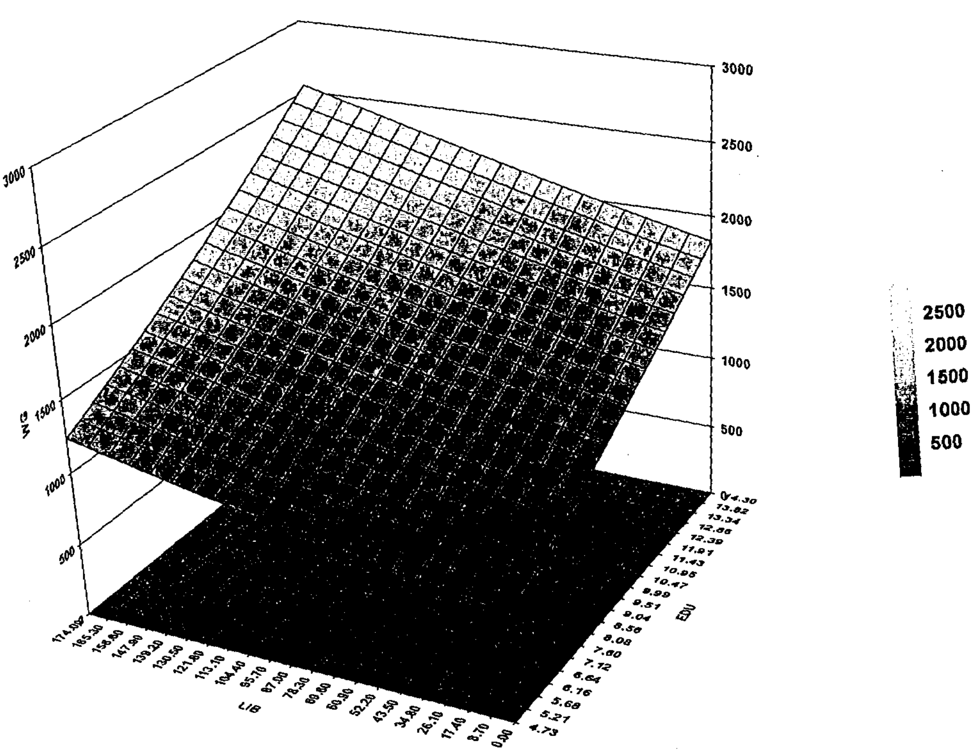

Appendix 6 (cont.)



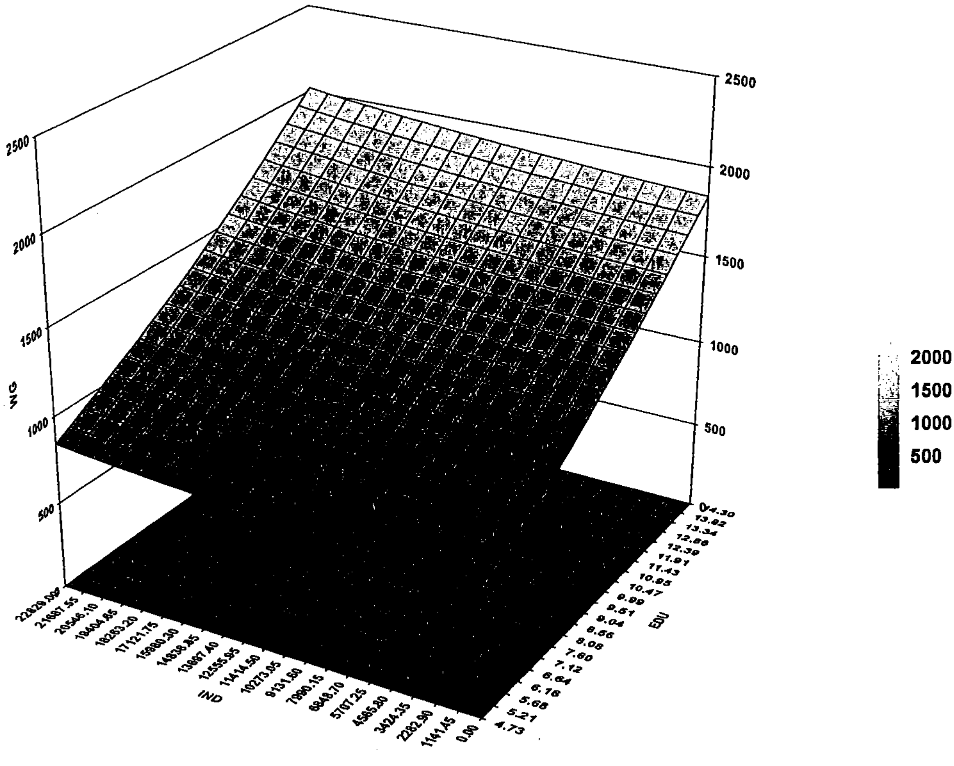



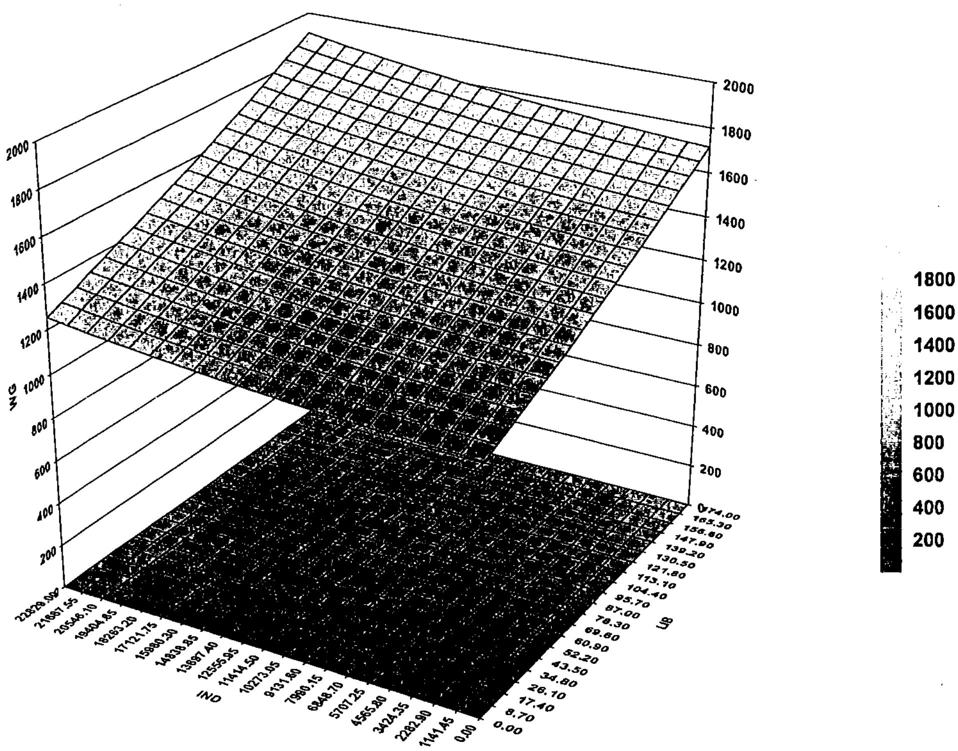

Appendix 6 (cont.)





Appendix 6 (cont.)




NeuroShell 2 – Release 4.0 (1993-1998) by Ward Systems Group®, Inc.
Licensed to Lincoln University.
Appendix 6 (cont.)

# APPENDIX 7

Analysis of Variance of the Multiple Linear Regression Model

VARIANCE ANALYSIS AND HYPOTHESIS TEST

Model: MODEL1
Dependent Variable: WG

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Prob>F |
|---|---|---|---|---|---|
| Model | 5 | 3.56226 | 0.71245 | 234.794 | 0.0001 |
| Error | 336 | 1.01955 | 0.00303 | | |
| C Total | 341 | 4.58181 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 0.05509 | R-square | 0.7775 |
| Dep Mean | 0.05773 | Adj R-sq | 0.7742 |
| C.V. | 95.42176 | | |

Parameter Estimates

| Variable | DF | Parameter Estimate | Standard Error | T for H0: Parameter=0 | Prob > \|T\| |
|---|---|---|---|---|---|
| INTERCEP | 1 | -0.005297 | 0.02758789 | -0.192 | 0.8479 |
| POP | 1 | 0.814134 | 0.03967624 | 20.519 | 0.0001 |
| PUP | 1 | 0.021068 | 0.01243142 | 1.695 | 0.0910 |
| EDU | 1 | -0.012185 | 0.04948936 | -0.246 | 0.8057 |
| LIB | 1 | -0.087319 | 0.05134120 | -1.701 | 0.0899 |
| IND | 1 | -0.120912 | 0.03142940 | -3.847 | 0.0001 |

Model: WLS
Dependent Variable: ABSUHAT

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Prob>F |
|---|---|---|---|---|---|
| Model | 5 | 0.17250 | 0.03450 | 16.366 | 0.0001 |
| Error | 336 | 0.70829 | 0.00211 | | |
| C Total | 341 | 0.88079 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 0.04591 | R-square | 0.1958 |
| Dep Mean | 0.02014 | Adj R-sq | 0.1839 |
| C.V. | 227.93960 | | |

Parameter Estimates

| Variable | DF | Parameter Estimate | Standard Error | T for H0: Parameter=0 | Prob > \|T\| |
|---|---|---|---|---|---|
| INTERCEP | 1 | 0.014024 | 0.02299433 | 0.610 | 0.5424 |
| POP | 1 | 0.197678 | 0.03306990 | 5.978 | 0.0001 |
| PUP | 1 | 0.010223 | 0.01036151 | 0.987 | 0.3245 |
| EDU | 1 | -0.017883 | 0.04124907 | -0.434 | 0.6649 |
| LIB | 1 | -0.038882 | 0.04279257 | -0.909 | 0.3642 |
| IND | 1 | -0.054104 | 0.02619621 | -2.065 | 0.0397 |

```
Model: MODEL1
NOTE: No intercept in model. R-square is redefined.
Dependent Variable: WGW

Analysis of Variance
                         Sum of          Mean
Source          DF      Squares        Square       F Value       Prob>F

Model            6   1689.38389     281.56398        89.380       0.0001
Error          336   1058.46449       3.15019
U Total        342   2747.84838

    Root MSE       1.77488     R-square        0.6148
    Dep Mean       1.76617     Adj R-sq        0.6079
    C.V.         100.49319

Parameter Estimates
                    Parameter       Standard     T for H0:
Variable  DF         Estimate          Error   Parameter=0    Prob > |T|

CW         1        -0.018260     0.00917240        -1.991        0.0473
POPW       1         0.646656     0.05151975        12.552        0.0001
PUPW       1         0.000037     0.00416389         0.009        0.9928
EDUW       1         0.026783     0.01539216         1.740        0.0828
LIBW       1         0.032282     0.06529686         0.494        0.6214
INDW       1        -0.042246     0.01428364        -2.958        0.0033


TITLE 'VARIANCE ANALYSIS AND HYPOTHESIS TEST';
OPTIONS LINESIZE=72 NODATE NONUMBER NOCENTER;
DATA ONE;                                               *create a data set;
INFILE 'E:\Eduardo\Research\Thesis\Part1\1.1 Data Processing\Model
3\Scaled Data 2\data.prn';
INPUT WG POP PUP EDU LIB IND;                               *input variables;

PROC REG;                                           *estimate the regression;
MODEL WG = POP PUP EDU LIB IND;                          *UNRESTRICTED MODEL;
OUTPUT OUT=OUT1 R=UHAT;     * UHAT is the residuals from the regression;

DATA TWO; SET OUT1;
ABSUHAT=ABS(UHAT);

PROC REG DATA=TWO;
WLS: MODEL ABSUHAT = POP PUP EDU LIB IND;

DATA WLS; SET TWO;
WG_W=0.014024+0.197678*POP+0.010223*PUP-0.017883*EDU-0.038882*LIB-
0.054104*IND;
WGW=WG/WG_W; POPW=POP/WG_W; PUPW=PUP/WG_W; EDUW=EDU/WG_W; LIBW=LIB/WG_W;
INDW=IND/WG_W; CW=1/WG_W;  *Transform the variables;

PROC REG DATA=WLS;    *Estimate the weighted least squares (WLS);

MODEL WGW = CW POPW PUPW EDUW LIBW INDW / NOINT;   *specify a model
without a constant term;

RUN;
```



Appendix 7 (cont.)

# APPENDIX 8

Self-Organising Feature Map

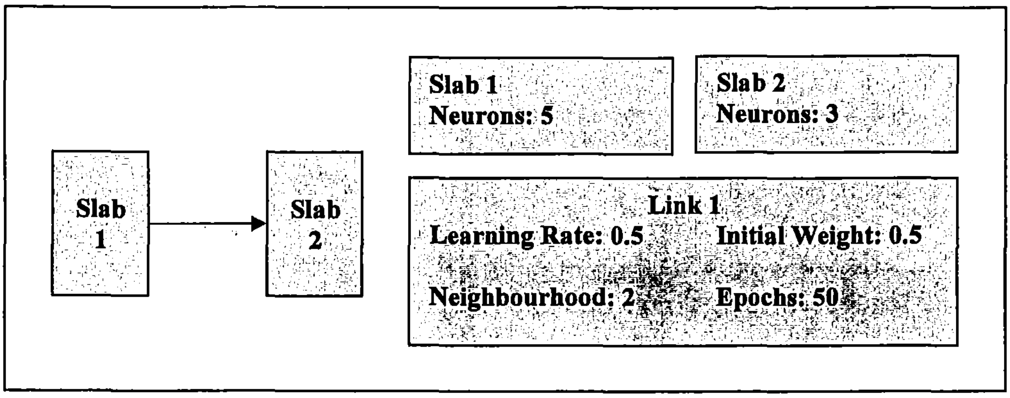



Figure A8.1: Self-Organising Map Architecture and Parameters

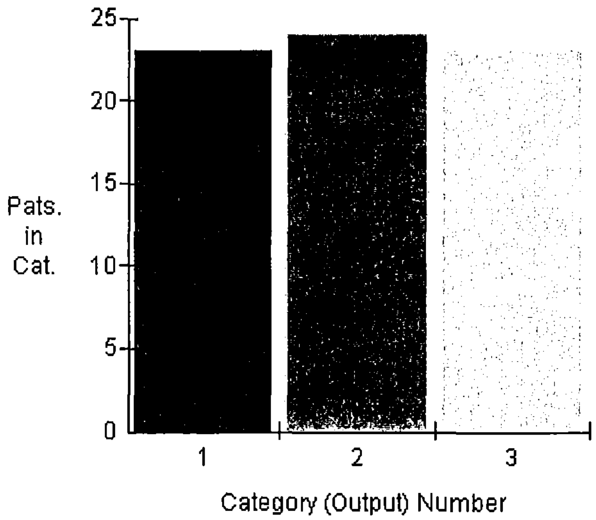



Figure A8.2: The SOFM Categories for the Validation Set

Table A8.1: Weights from Each of the 5 Input Neurons to Each of the 3 Output Neurons

| Weights | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | 0.3881058 | 0.1165717 | 0.4193836 | 0.1061983 | 0.3323979 |
| 2 | 0.6017114 | 0.5459712 | 0.4155394 | 0.2220777 | 0.5456206 |
| 3 | 0.7828287 | 0.9219683 | 0.5825663 | 0.4108890 | 0.5869827 |

NeuroShell 2 – Release 4.0 (1993-1998) by Ward Systems Group®, Inc.
Licensed to Lincoln University.

# APPENDIX 9

Clusters of Communes and their Respective Values for the Five Most Relevant Variables Contributing to Waste Generation

# Table A9.1: SOFM Output Categories

| | Network(1) | Network(2) | Network(3) | | Network(1) | Network(2) | Network(3) | | Network(1) | Network(2) | Network(3) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Arica | 0 | 0 | 1 | Vichuquén | 1 | 0 | 0 | Lanco | 0 | 1 | 0 |
| General Lagos | 1 | 0 | 0 | Licantén | 0 | 1 | 0 | Panguipulli | 0 | 1 | 0 |
| Putre | 1 | 0 | 0 | Hualañé | 0 | 1 | 0 | Máfil | 0 | 1 | 0 |
| Camarones | 1 | 0 | 0 | Rauco | 0 | 1 | 0 | Valdivia | 0 | 0 | 1 |
| Huara | 1 | 0 | 0 | Sagrada Familia | 0 | 1 | 0 | Los Lagos | 0 | 1 | 0 |
| Camiña | 1 | 0 | 0 | Teno | 0 | 1 | 0 | Futrono | 0 | 1 | 0 |
| Colchane | 1 | 0 | 0 | Curicó | 0 | 0 | 1 | Corral | 0 | 1 | 0 |
| Iquique | 0 | 0 | 1 | Molina | 0 | 1 | 0 | Paillaco | 0 | 1 | 0 |
| Pozo Almonte | 0 | 1 | 0 | Romeral | 1 | 0 | 0 | La Unión | 0 | 1 | 0 |
| Pica | 0 | 1 | 0 | Curepto | 1 | 0 | 0 | Lago Ranco | 1 | 0 | 0 |
| Tocopilla | 0 | 0 | 1 | Constitución | 0 | 1 | 0 | RíoBueno | 0 | 1 | 0 |
| María Elena | 0 | 0 | 1 | Empedrado | 0 | 1 | 0 | San Juan de la Costa | 1 | 0 | 0 |
| Calama | 0 | 0 | 1 | Pencahue | 1 | 0 | 0 | San Pablo | 1 | 0 | 0 |
| Ollagüe | 1 | 0 | 0 | San Rafael | 0 | 1 | 0 | Osorno | 0 | 0 | 1 |
| Mejillones | 0 | 1 | 0 | Talca | 0 | 0 | 1 | Puyehue | 0 | 1 | 0 |
| Sierra Gorda | 1 | 0 | 0 | Maule | 1 | 0 | 0 | Río Negro | 0 | 1 | 0 |
| San Pedro de Atacama | 1 | 0 | 0 | Río Claro | 1 | 0 | 0 | Purranque | 0 | 1 | 0 |
| Antofagasta | 0 | 0 | 1 | Pelarco | 1 | 0 | 0 | Puerto Octay | 1 | 0 | 0 |
| Taltal | 0 | 0 | 1 | San Clemente | 0 | 1 | 0 | Fresia | 0 | 1 | 0 |
| Chañaral | 0 | 0 | 1 | Chanco | 0 | 1 | 0 | Frutillar | 0 | 1 | 0 |
| Diego de Almagro | 0 | 0 | 1 | Pelluhue | 1 | 0 | 0 | Puerto Varas | 0 | 1 | 0 |
| Caldera | 0 | 0 | 1 | Cauquenes | 0 | 1 | 0 | Llanquihue | 0 | 1 | 0 |
| Copiapó | 0 | 0 | 1 | San Javier | 0 | 1 | 0 | Los Muermos | 1 | 0 | 0 |
| Tierra Amarilla | 0 | 1 | 0 | Retiro | 1 | 0 | 0 | Puerto Montt | 0 | 0 | 1 |
| Huasco | 0 | 1 | 0 | Parral | 0 | 1 | 0 | Maullín | 0 | 1 | 0 |
| Freirina | 0 | 1 | 0 | Villa Alegre | 0 | 1 | 0 | Calbuco | 0 | 1 | 0 |
| Vallenar | 0 | 0 | 1 | Linares | 0 | 0 | 1 | Cochamó | 1 | 0 | 0 |
| Alto del Carmen | 1 | 0 | 0 | Longaví | 0 | 1 | 0 | Ancud | 0 | 1 | 0 |
| La Higuera | 1 | 0 | 0 | Yerbas Buenas | 1 | 0 | 0 | Dalcahue | 1 | 0 | 0 |
| La Serena | 0 | 0 | 1 | Colbún | 0 | 1 | 0 | Quemchi | 1 | 0 | 0 |
| Vicuña | 0 | 1 | 0 | Cobquecura | 1 | 0 | 0 | Castro | 0 | 1 | 0 |
| Coquimbo | 0 | 0 | 1 | Quirihue | 0 | 1 | 0 | Quinchao | 1 | 0 | 0 |
| Andacollo | 0 | 1 | 0 | Ninhue | 1 | 0 | 0 | Curaco De Vélez | 1 | 0 | 0 |
| RíoHurtado | 1 | 0 | 0 | San Carlos | 0 | 1 | 0 | Chonchi | 0 | 1 | 0 |
| Paihuano | 1 | 0 | 0 | Ñiquén | 1 | 0 | 0 | Puqueldón | 1 | 0 | 0 |
| Ovalle | 0 | 0 | 1 | San Fabián | 1 | 0 | 0 | Queilén | 1 | 0 | 0 |
| Punitaqui | 0 | 1 | 0 | Trehuaco | 1 | 0 | 0 | Quellón | 0 | 1 | 0 |
| Monte Patria | 0 | 1 | 0 | Coelemu | 0 | 1 | 0 | Hualaihué | 1 | 0 | 0 |
| Combarbalá | 0 | 1 | 0 | Portezuelo | 1 | 0 | 0 | Chaitén | 0 | 1 | 0 |
| Canela | 1 | 0 | 0 | Ránquil | 1 | 0 | 0 | Futaleufú | 0 | 1 | 0 |
| Illapel | 0 | 1 | 0 | San Nicolás | 1 | 0 | 0 | Palena | 1 | 0 | 0 |
| Los Vilos | 0 | 1 | 0 | Chillán | 0 | 0 | 1 | Guaitecas | 1 | 0 | 0 |
| Salamanca | 0 | 1 | 0 | Chillán Viejo | 0 | 1 | 0 | Cisnes | 1 | 0 | 0 |
| La Ligua | 0 | 1 | 0 | Bulnes | 0 | 1 | 0 | Lago Verde | 1 | 0 | 0 |
| Petorca | 1 | 0 | 0 | Quillón | 0 | 1 | 0 | Puerto Aysén | 0 | 1 | 0 |
| Cabildo | 0 | 1 | 0 | Pemuco | 0 | 1 | 0 | Coihaique | 0 | 0 | 1 |
| Putaendo | 0 | 1 | 0 | Coihueco | 0 | 1 | 0 | Río Ibáñez | 1 | 0 | 0 |
| San Esteban | 0 | 1 | 0 | Pinto | 0 | 1 | 0 | Chile Chico | 0 | 1 | 0 |
| Los Andes | 0 | 0 | 1 | San Ignacio | 1 | 0 | 0 | Tortel | 1 | 0 | 0 |
| Papudo | 0 | 1 | 0 | El Carmen | 1 | 0 | 0 | Cochrane | 0 | 1 | 0 |
| Zapallar | 1 | 0 | 0 | Yungay | 0 | 1 | 0 | O'Higgins | 1 | 0 | 0 |
| Puchuncaví | 0 | 1 | 0 | Tomé | 0 | 0 | 1 | Puerto Natales | 0 | 1 | 0 |
| Nogales | 0 | 1 | 0 | Florida | 0 | 1 | 0 | Torres del Paine | 1 | 0 | 0 |
| Catemu | 0 | 1 | 0 | Penco | 0 | 0 | 1 | Río Verde | 1 | 0 | 0 |
| San Felipe | 0 | 0 | 1 | Concepción | 0 | 0 | 1 | Laguna Blanca | 1 | 0 | 0 |
| Santa María | 0 | 1 | 0 | Talcahuano | 0 | 0 | 1 | San Gregorio | 1 | 0 | 0 |
| Quintero | 0 | 0 | 1 | San Pedro de la Paz | 0 | 0 | 1 | Punta Arenas | 0 | 0 | 1 |
| La Cruz | 0 | 1 | 0 | Chiguayante | 0 | 0 | 1 | Primavera | 1 | 0 | 0 |
| Calera | 0 | 0 | 1 | Coronel | 0 | 0 | 1 | Porvenir | 0 | 1 | 0 |
| Hijuelas | 0 | 1 | 0 | Hualqui | 0 | 1 | 0 | Timaukel | 1 | 0 | 0 |
| Panquehue | 0 | 1 | 0 | Lota | 0 | 0 | 1 | Navarino | 0 | 1 | 0 |
| Rinconada | 0 | 1 | 0 | Santa Juana | 0 | 1 | 0 | Antártica | 1 | 0 | 0 |
| Calle Larga | 1 | 0 | 0 | Yumbel | 0 | 1 | 0 | Tiltil | 0 | 1 | 0 |
| Llaillay | 0 | 1 | 0 | Cabrero | 0 | 1 | 0 | Colina | 0 | 0 | 1 |
| Quillota | 0 | 0 | 1 | San Rosendo | 0 | 1 | 0 | Lampa | 0 | 1 | 0 |

| | Network(1) | Network(2) | Network(3) | | Network(1) | Network(2) | Network(3) | | Network(1) | Network(2) | Network(3) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Concón | 0 | 0 | 1 | Laja | 0 | 1 | 0 | Curacaví | 0 | 1 | 0 |
| Limache | 0 | 0 | 1 | Nacimiento | 0 | 1 | 0 | María Pinto | 1 | 0 | 0 |
| Olmué | 0 | 1 | 0 | Los Angeles | 0 | 0 | 1 | Melipilla | 0 | 0 | 1 |
| Viña del Mar | 0 | 0 | 1 | Quilleco | 0 | 1 | 0 | San Pedro | 1 | 0 | 0 |
| Quilpué | 0 | 0 | 1 | Tucapel | 0 | 1 | 0 | Alhué | 1 | 0 | 0 |
| Villa Alemana | 0 | 0 | 1 | Antuco | 1 | 0 | 0 | Paine | 0 | 1 | 0 |
| Valparaiso | 0 | 0 | 1 | Santa Bárbara | 0 | 1 | 0 | Buin | 0 | 0 | 1 |
| Casablanca | 0 | 1 | 0 | Quilaco | 1 | 0 | 0 | San Bernardo | 0 | 0 | 1 |
| Algarrobo | 0 | 1 | 0 | Mulchén | 0 | 1 | 0 | Calera de Tango | 0 | 1 | 0 |
| El Quisco | 0 | 0 | 1 | Negrete | 0 | 1 | 0 | Padre Hurtado | 0 | 0 | 1 |
| El Tabo | 0 | 1 | 0 | Arauco | 0 | 1 | 0 | Peñaflor | 0 | 0 | 1 |
| Cartagena | 0 | 0 | 1 | Curanilahue | 0 | 0 | 1 | El Monte | 0 | 0 | 1 |
| San Antonio | 0 | 0 | 1 | Lebu | 0 | 1 | 0 | Talagante | 0 | 0 | 1 |
| Santo Domingo | 1 | 0 | 0 | Los Alamos | 0 | 1 | 0 | Isla de Maipo | 0 | 1 | 0 |
| Juan Fernández | 1 | 0 | 0 | Cañete | 0 | 1 | 0 | San José de Maipo | 0 | 1 | 0 |
| Isla de Pascua | 0 | 0 | 1 | Contulmo | 1 | 0 | 0 | Puente Alto | 0 | 0 | 1 |
| Navidad | 1 | 0 | 0 | Tirúa | 1 | 0 | 0 | Pirque | 1 | 0 | 0 |
| Litueche | 1 | 0 | 0 | Angol | 0 | 0 | 1 | Lo Barnechea | 0 | 0 | 1 |
| Las Cabras | 0 | 1 | 0 | Renaico | 0 | 1 | 0 | Vitacura | 0 | 0 | 1 |
| Coltauco | 1 | 0 | 0 | Collipulli | 0 | 1 | 0 | Las Condes | 0 | 0 | 1 |
| Doñihue | 0 | 1 | 0 | Lonquimay | 0 | 1 | 0 | La Reina | 0 | 0 | 1 |
| Rancagua | 0 | 0 | 1 | Purén | 0 | 1 | 0 | Peñalolén | 0 | 0 | 1 |
| Graneros | 0 | 1 | 0 | Los Sauces | 0 | 1 | 0 | La Florida | 0 | 0 | 1 |
| Mostazal | 0 | 1 | 0 | Ercilla | 0 | 1 | 0 | Huechuraba | 0 | 0 | 1 |
| La Estrella | 1 | 0 | 0 | Lumaco | 0 | 1 | 0 | Recoleta | 0 | 0 | 1 |
| Pichilemu | 0 | 1 | 0 | Traiguén | 0 | 1 | 0 | Providencia | 0 | 0 | 1 |
| Marchihue | 1 | 0 | 0 | Victoria | 0 | 1 | 0 | Ñuñoa | 0 | 0 | 1 |
| Paredones | 1 | 0 | 0 | Curacautín | 0 | 1 | 0 | Macul | 0 | 0 | 1 |
| Pichidegua | 1 | 0 | 0 | Carahue | 0 | 1 | 0 | Conchalí | 0 | 0 | 1 |
| Peumo | 0 | 1 | 0 | Nueva Imperial | 0 | 1 | 0 | Independencia | 0 | 0 | 1 |
| San Vicente | 0 | 1 | 0 | Galvarino | 1 | 0 | 0 | Santiago | 0 | 0 | 1 |
| Coinco | 0 | 1 | 0 | Perquenco | 0 | 1 | 0 | San Joaquín | 0 | 0 | 1 |
| Quinta de Tilcoco | 0 | 1 | 0 | Lautaro | 0 | 1 | 0 | La Granja | 0 | 0 | 1 |
| Olivar | 0 | 1 | 0 | Vilcún | 0 | 1 | 0 | San Ramón | 0 | 0 | 1 |
| Requinoa | 1 | 0 | 0 | Melipeuco | 1 | 0 | 0 | La Pintana | 0 | 0 | 1 |
| Rengo | 0 | 1 | 0 | Temuco | 0 | 0 | 1 | San Miguel | 0 | 0 | 1 |
| Malloa | 0 | 1 | 0 | Padre Las Casas | 0 | 1 | 0 | La Cisterna | 0 | 0 | 1 |
| Codegua | 0 | 1 | 0 | Saavedra | 1 | 0 | 0 | El Bosque | 0 | 0 | 1 |
| Machalí | 0 | 0 | 1 | Teodoro Schmidt | 0 | 1 | 0 | Pedro Aguirre Cerda | 0 | 0 | 1 |
| Peralillo | 0 | 1 | 0 | Freire | 0 | 1 | 0 | Lo Espejo | 0 | 0 | 1 |
| Pumanque | 1 | 0 | 0 | Cunco | 0 | 1 | 0 | Quilicura | 0 | 0 | 1 |
| Lolol | 1 | 0 | 0 | Toltén | 1 | 0 | 0 | Renca | 0 | 0 | 1 |
| Palmilla | 1 | 0 | 0 | Pitrufquén | 0 | 1 | 0 | Quinta Normal | 0 | 0 | 1 |
| Santa Cruz | 0 | 1 | 0 | Gorbea | 0 | 1 | 0 | Cerro Navia | 0 | 0 | 1 |
| Chépica | 0 | 1 | 0 | Loncoche | 0 | 1 | 0 | Lo Prado | 0 | 0 | 1 |
| Nancagua | 0 | 1 | 0 | Villarrica | 0 | 1 | 0 | Estación Central | 0 | 0 | 1 |
| Placilla | 1 | 0 | 0 | Pucón | 0 | 1 | 0 | Cerrillos | 0 | 0 | 1 |
| Chimbarongo | 0 | 1 | 0 | Curarrehue | 1 | 0 | 0 | Pudahuel | 0 | 0 | 1 |
| San Fernando | 0 | 0 | 1 | Mariquina | 0 | 1 | 0 | Maipú | 0 | 0 | 1 |

Table A9.2: Data Group 1

| GROUP 1 | WG (tonnes/month) | POP (people) | PUP (*100) | EDU (number) | LIB (number) | IND (people) |
|---|---|---|---|---|---|---|
| General Lagos | 0.60 | 1,179 | 0.00 | 4.7 | 0 | 74 |
| Putre | 4.00 | 1,977 | 0.43 | 5.9 | 2 | 144 |
| Camarones | 3.00 | 1,220 | 0.00 | 6.3 | 0 | 82 |
| Huara | 16.00 | 2,599 | 0.00 | 7.5 | 0 | 86 |
| Camiña | 8.00 | 1,275 | 0.00 | 6.3 | 0 | 206 |
| Colchane | 0.00 | 1,649 | 0.00 | 5.2 | 0 | 359 |
| Ollagüe | 1.60 | 318 | 0.00 | 9.3 | 1 | 9 |
| Sierra Gorda | 42.00 | 2,356 | 0.00 | 9.3 | 2 | 66 |
| San Pedro de Atacama | 32.50 | 4,969 | 0.00 | 7.4 | 2 | 97 |
| Alto del Carmen | 3.50 | 4,840 | 0.00 | 6.8 | 1 | 183 |
| La Higuera | 39.50 | 3,721 | 0.00 | 6.1 | 1 | 168 |
| RíoHurtado | 45.00 | 4,771 | 0.00 | 6.3 | 0 | 312 |
| Paihuano | 116.16 | 4,168 | 0.00 | 8.1 | 0 | 182 |
| Canela | 150.00 | 9,379 | 0.13 | 6.1 | 1 | 1,721 |
| Petorca | 136.00 | 9,440 | 0.30 | 7.9 | 1 | 480 |
| Zapallar | 78.78 | 5,659 | 0.54 | 8.0 | 0 | 0 |
| Calle Larga | 280.50 | 10,393 | 0.49 | 8.2 | 1 | 0 |
| Santo Domingo | 295.85 | 7,418 | 0.33 | 8.5 | 0 | 0 |
| Juan Fernández | 17.93 | 633 | 0.00 | 9.0 | 0 | 20 |
| Navidad | 50.00 | 5,422 | 0.10 | 8.3 | 1 | 286 |
| Litueche | 54.00 | 5,526 | 0.34 | 8.3 | 0 | 292 |
| Coltauco | 252.00 | 16,228 | 0.12 | 8.3 | 4 | 857 |
| La Estrella | 20.00 | 4,221 | 0.00 | 8.3 | 1 | 223 |
| Marchihue | 55.00 | 6,904 | 0.28 | 8.3 | 1 | 365 |
| Paredones | 48.00 | 6,695 | 0.26 | 8.3 | 1 | 353 |
| Pichidegua | 182.00 | 17,756 | 0.26 | 8.3 | 0 | 937 |
| Requinoa | 610.56 | 22,161 | 0.45 | 7.6 | 1 | 0 |
| Pumanque | 40.00 | 3,442 | 0.00 | 8.3 | 0 | 182 |
| Lolol | 30.00 | 6,191 | 0.28 | 8.3 | 0 | 327 |
| Palmilla | 60.00 | 11,200 | 0.16 | 8.3 | 0 | 591 |
| Placilla | 36.32 | 8,078 | 0.21 | 8.3 | 0 | 427 |
| Vichuquén | 54.00 | 4,916 | 0.00 | 8.0 | 0 | 286 |
| Romeral | 116.55 | 12,707 | 0.22 | 8.0 | 0 | 740 |
| Curepto | 51.00 | 10,812 | 0.24 | 8.0 | 2 | 629 |
| Pencahue | 34.58 | 8,315 | 0.14 | 8.0 | 1 | 484 |
| Maule | 70.20 | 16,837 | 0.20 | 8.0 | 0 | 980 |
| Río Claro | 62.00 | 12,698 | 0.20 | 8.0 | 0 | 739 |
| Pelarco | 26.00 | 7,266 | 0.21 | 8.0 | 0 | 423 |
| Pelluhue | 30.00 | 6,414 | 0.26 | 8.0 | 0 | 373 |
| Retiro | 686.54 | 18,487 | 0.17 | 8.0 | 1 | 1,076 |
| Yerbas Buenas | 486.79 | 16,134 | 0.10 | 8.0 | 1 | 939 |
| Cobquecura | 74.80 | 5,687 | 0.17 | 8.8 | 1 | 439 |
| Ninhue | 41.30 | 5,738 | 0.17 | 8.8 | 1 | 443 |
| Ñiquén | 41.30 | 11,421 | 0.09 | 8.8 | 2 | 881 |
| San Fabián | 28.00 | 3,646 | 0.34 | 8.8 | 1 | 281 |
| Trehuaco | 72.09 | 5,296 | 0.00 | 8.8 | 0 | 408 |
| Portezuelo | 43.20 | 5,470 | 0.25 | 8.8 | 0 | 422 |
| Ránquil | 47.50 | 5,683 | 0.23 | 8.8 | 1 | 438 |
| San Nicolás | 111.00 | 9,741 | 0.28 | 8.8 | 1 | 751 |
| San Ignacio | 12.00 | 16,106 | 0.15 | 8.8 | 1 | 1,242 |
| El Carmen | 113.30 | 12,845 | 0.25 | 8.8 | 0 | 991 |
| Antuco | 75.30 | 3,908 | 0.37 | 8.8 | 0 | 301 |
| Quilaco | 64.60 | 4,021 | 0.29 | 8.8 | 1 | 310 |
| Contulmo | 78.35 | 5,838 | 0.31 | 8.8 | 1 | 450 |
| Tirúa | 129.69 | 9,664 | 0.19 | 8.8 | 2 | 745 |
| Galvarino | 244.63 | 12,596 | 0.23 | 7.8 | 1 | 1,344 |
| Melipeuco | 27.00 | 5,628 | 0.37 | 7.8 | 0 | 601 |
| Saavedra | 52.00 | 14,034 | 0.16 | 7.8 | 2 | 1,498 |
| Toltén | 217.83 | 11,216 | 0.19 | 7.8 | 1 | 1,197 |
| Curarrehue | 252.96 | 6,784 | 0.23 | 6.3 | 0 | 583 |
| Lago Ranco | 40.80 | 10,098 | 0.19 | 9.2 | 1 | 679 |
| San Juan de la Costa | 308.00 | 8,831 | 0.10 | 9.2 | 0 | 593 |
| San Pablo | 357.28 | 10,162 | 0.26 | 9.2 | 2 | 683 |
| Puerto Octay | 96.00 | 10,236 | 0.26 | 9.2 | 1 | 688 |
| Los Muermos | 30.00 | 16,964 | 0.22 | 9.2 | 1 | 1,140 |
| Cochamó | 70.20 | 4,363 | 0.00 | 9.2 | 1 | 293 |
| Dalcahue | 396.00 | 10,693 | 0.29 | 9.2 | 0 | 719 |
| Quemchi | 35.00 | 8,689 | 0.17 | 9.2 | 2 | 584 |
| Quinchao | 240.00 | 8,976 | 0.27 | 9.2 | 1 | 603 |
| Curaco De Vélez | 540.00 | 3,403 | 0.00 | 9.2 | 0 | 229 |
| Puqueldón | 38.40 | 4,160 | 0.00 | 9.2 | 1 | 280 |
| Queilén | 151.20 | 5,138 | 0.27 | 9.2 | 0 | 345 |
| Hualaihué | 158.40 | 8,273 | 0.14 | 9.2 | 1 | 556 |
| Palena | 16.00 | 1,690 | 0.00 | 9.2 | 1 | 114 |
| Guaitecas | 27.20 | 1,539 | 0.00 | 8.3 | 0 | 0 |
| Cisnes | 101.43 | 5,739 | 0.33 | 8.3 | 3 | 0 |
| Lago Verde | 18.77 | 1,062 | 0.00 | 8.3 | 1 | 0 |
| Río Ibáñez | 43.78 | 2,477 | 0.00 | 8.3 | 3 | 0 |
| Tortel | 8.96 | 507 | 0.00 | 8.3 | 1 | 0 |
| O'Higgins | 8.18 | 463 | 0.00 | 8.3 | 0 | 0 |
| Torres del Paine | 3.75 | 739 | 0.00 | 8.7 | 1 | 0 |
| Río Verde | 0.45 | 358 | 0.00 | 8.7 | 1 | 0 |
| Laguna Blanca | 10.00 | 663 | 0.00 | 8.7 | 0 | 0 |
| San Gregorio | 30.00 | 1,158 | 0.00 | 8.7 | 0 | 0 |
| Primavera | 96.00 | 1,016 | 0.00 | 8.7 | 0 | 0 |
| Timaukel | 2.00 | 423 | 0.00 | 8.7 | 0 | 0 |
| Antártica | 9.16 | 130 | 0.00 | 8.7 | 3 | 0 |
| Maria Pinto | 37.24 | 10,343 | 0.13 | 7.5 | 1 | 813 |
| San Pedro | 27.18 | 7,549 | 0.00 | 6.7 | 1 | 447 |
| Alhué | 21.00 | 4,435 | 0.00 | 6.7 | 1 | 276 |
| Pirque | 514.80 | 16,565 | 0.23 | 9.3 | 3 | 459 |

## Table A9.3: Data Group 2

| GROUP 2 | WG (tonnes/month) | POP (people) | PUP (*100) | EDU (number) | LIB (number) | IND (people) |
|---|---|---|---|---|---|---|
| Pozo Almonte | 15.00 | 10,830 | 0.63 | 9.3 | 1 | 213 |
| Pica | 10.00 | 6,178 | 0.70 | 8.7 | 4 | 84 |
| Mejillones | 1,444.00 | 8,418 | 0.88 | 9.3 | 1 | 320 |
| Tierra Amarilla | 120.00 | 12,888 | 0.67 | 8.6 | 4 | 1,200 |
| Huasco | 90.00 | 7,945 | 0.81 | 9.2 | 4 | 399 |
| Freirina | 80.00 | 5,666 | 0.61 | 7.7 | 1 | 355 |
| Vicuña | 584.50 | 24,010 | 0.36 | 7.9 | 2 | 505 |
| Andacollo | 90.50 | 10,288 | 0.83 | 7.9 | 2 | 471 |
| Punitaqui | 112.00 | 9,539 | 0.27 | 7.1 | 1 | 1,406 |
| Monte Patria | 360.00 | 30,276 | 0.33 | 6.6 | 2 | 2,573 |
| Combarbalá | 180.00 | 13,483 | 0.34 | 7.0 | 2 | 1,311 |
| Illapel | 540.00 | 30,355 | 0.65 | 8.4 | 6 | 2,941 |
| Los Vilos | 400.00 | 17,453 | 0.65 | 7.9 | 2 | 1,044 |
| Salamanca | 540.00 | 24,494 | 0.41 | 7.1 | 2 | 2,154 |
| La Ligua | 460.56 | 31,987 | 0.71 | 8.9 | 4 | 1,760 |
| Cabildo | 273.00 | 18,916 | 0.61 | 7.9 | 1 | 1,424 |
| Putaendo | 540.00 | 14,649 | 0.47 | 7.8 | 1 | 811 |
| San Esteban | 408.00 | 14,400 | 0.41 | 8.5 | 1 | 956 |
| Papudo | 66.66 | 4,608 | 0.93 | 8.4 | 0 | 291 |
| Puchuncaví | 359.00 | 12,954 | 0.82 | 8.0 | 3 | 1,498 |
| Nogales | 370.11 | 21,633 | 0.78 | 8.3 | 2 | 1,857 |
| Catemu | 432.00 | 12,112 | 0.54 | 8.1 | 1 | 412 |
| Santa María | 420.00 | 12,813 | 0.47 | 8.8 | 1 | 672 |
| La Cruz | 236.39 | 12,851 | 0.78 | 10.0 | 1 | 0 |
| Hijuelas | 284.70 | 16,014 | 0.48 | 7.4 | 2 | 845 |
| Panquehue | 252.00 | 6,567 | 0.42 | 7.9 | 0 | 472 |
| Rinconada | 178.50 | 6,692 | 0.79 | 8.0 | 1 | 515 |
| Llaillay | 744.90 | 21,644 | 0.75 | 8.9 | 2 | 1,013 |
| Olmué | 236.39 | 14,105 | 0.68 | 8.5 | 1 | 868 |
| Casablanca | 609.00 | 21,874 | 0.62 | 8.8 | 1 | 0 |
| Algarrobo | 341.05 | 8,601 | 0.76 | 8.7 | 0 | 0 |
| El Tabo | 842.02 | 7,028 | 0.93 | 8.9 | 1 | 0 |
| Las Cabras | 375.00 | 20,242 | 0.34 | 8.3 | 2 | 1,069 |
| Doñihue | 466.08 | 16,916 | 0.78 | 8.3 | 2 | 893 |
| Graneros | 715.32 | 25,961 | 0.79 | 8.6 | 1 | 2,022 |
| Mostazal | 602.40 | 21,866 | 0.76 | 8.0 | 2 | 1,824 |
| Pichilemu | 110.00 | 12,392 | 0.65 | 7.8 | 1 | 988 |
| Peumo | 384.24 | 13,948 | 0.52 | 8.3 | 1 | 736 |
| San Vicente | 580.00 | 40,253 | 0.39 | 8.1 | 0 | 1,529 |
| Coínco | 175.92 | 6,385 | 0.43 | 8.3 | 1 | 337 |
| Quinta de Tilcoco | 313.56 | 11,380 | 0.47 | 8.3 | 1 | 601 |
| Olivar | 339.84 | 12,335 | 0.68 | 8.3 | 1 | 651 |
| Rengo | 1,400.40 | 50,830 | 0.65 | 8.1 | 5 | 4,160 |
| Malloa | 125.00 | 12,872 | 0.36 | 8.3 | 1 | 680 |
| Codegua | 297.48 | 10,796 | 0.36 | 8.3 | 1 | 570 |
| Peralillo | 43.68 | 9,729 | 0.56 | 8.3 | 1 | 514 |
| Santa Cruz | 674.70 | 32,387 | 0.53 | 7.8 | 5 | 2,116 |
| Chépica | 288.68 | 13,857 | 0.45 | 6.8 | 1 | 1,697 |
| Nancagua | 325.70 | 15,634 | 0.57 | 7.7 | 1 | 0 |
| Chimbarongo | 673.22 | 32,316 | 0.38 | 7.4 | 2 | 630 |
| Licantén | 60.00 | 6,902 | 0.48 | 8.0 | 1 | 402 |
| Hualañé | 60.00 | 9,741 | 0.41 | 8.0 | 2 | 567 |
| Rauco | 235.20 | 8,566 | 0.33 | 8.0 | 1 | 1,020 |
| Sagrada Familia | 160.65 | 17,519 | 0.26 | 8.0 | 1 | 1,020 |
| Teno | 697.20 | 25,596 | 0.22 | 6.7 | 2 | 991 |
| Molina | 352.80 | 38,521 | 0.68 | 8.1 | 4 | 2,307 |
| Constitución | 240.00 | 46,081 | 0.77 | 7.4 | 5 | 9,004 |
| Empedrado | 50.22 | 4,225 | 0.49 | 8.0 | 1 | 246 |
| San Rafael | 50.00 | 7,674 | 0.41 | 8.0 | 0 | 447 |
| San Clemente | 155.22 | 37,261 | 0.30 | 6.5 | 1 | 3,752 |
| Chanco | 330.73 | 9,457 | 0.41 | 8.0 | 1 | 550 |
| Cauquenes | 489.78 | 41,217 | 0.68 | 7.4 | 4 | 2,546 |
| San Javier | 1,080.00 | 37,793 | 0.51 | 7.4 | 2 | 2,569 |
| Parral | 1,325.23 | 37,822 | 0.64 | 8.2 | 3 | 3,283 |
| Villa Alegre | 420.00 | 14,725 | 0.35 | 8.0 | 0 | 857 |
| Longaví | 814.80 | 28,161 | 0.20 | 8.0 | 1 | 1,639 |
| Colbún | 509.75 | 17,619 | 0.27 | 8.0 | 1 | 1,025 |
| Quirihue | 197.40 | 11,429 | 0.61 | 8.8 | 4 | 881 |
| San Carlos | 567.00 | 50,088 | 0.54 | 7.9 | 2 | 3,539 |
| Coelemu | 218.91 | 16,082 | 0.57 | 8.8 | 1 | 1,240 |
| Chillán Viejo | 696.00 | 22,084 | 0.78 | 8.9 | 1 | 1,716 |
| Bulnes | 7,000.00 | 20,595 | 0.47 | 8.8 | 3 | 1,588 |
| Quillón | 248.40 | 15,146 | 0.32 | 8.8 | 1 | 1,168 |
| Pemuco | 92.80 | 8,821 | 0.36 | 8.8 | 0 | 680 |
| Coihueco | 323.10 | 23,583 | 0.24 | 6.1 | 1 | 4,988 |
| Pinto | 111.30 | 9,875 | 0.40 | 8.8 | 2 | 762 |
| Yungay | 113.76 | 16,814 | 0.59 | 8.8 | 2 | 1,297 |
| Florida | 201.41 | 10,177 | 0.29 | 8.8 | 1 | 785 |
| Hualqui | 450.00 | 18,768 | 0.63 | 8.8 | 1 | 1,448 |
| Santa Juana | 179.70 | 12,713 | 0.45 | 8.8 | 2 | 981 |
| Yumbel | 138.68 | 20,498 | 0.46 | 8.8 | 2 | 1,581 |
| Cabrero | 171.06 | 25,282 | 0.64 | 8.8 | 3 | 1,950 |
| San Rosendo | 26.52 | 3,918 | 0.77 | 8.8 | 1 | 302 |
| Laja | 151.59 | 22,404 | 0.72 | 8.5 | 1 | 2,886 |
| Nacimiento | 378.70 | 25,971 | 0.73 | 7.9 | 3 | 4,904 |
| Quilleco | 147.60 | 10,428 | 0.36 | 8.8 | 1 | 804 |
| Tucapel | 86.45 | 12,777 | 0.59 | 8.8 | 3 | 985 |
| Santa Bárbara | 371.60 | 19,970 | 0.32 | 8.8 | 2 | 1,540 |
| Mulchén | 554.70 | 29,003 | 0.66 | 7.4 | 2 | 8,620 |
| Negrete | 125.10 | 8,579 | 0.47 | 8.8 | 2 | 662 |
| Arauco | 778.42 | 34,873 | 0.58 | 8.3 | 1 | 4,015 |
| Lebu | 520.70 | 25,035 | 0.80 | 7.8 | 0 | 3,172 |
| Los Alamos | 427.20 | 18,632 | 0.80 | 8.8 | 2 | 1,437 |
| Cañete | 419.66 | 31,270 | 0.53 | 7.0 | 2 | 5,068 |
| Renaico | 49.14 | 9,128 | 0.55 | 7.8 | 1 | 974 |
| Collipulli | 572.00 | 22,354 | 0.63 | 7.6 | 2 | 3,636 |

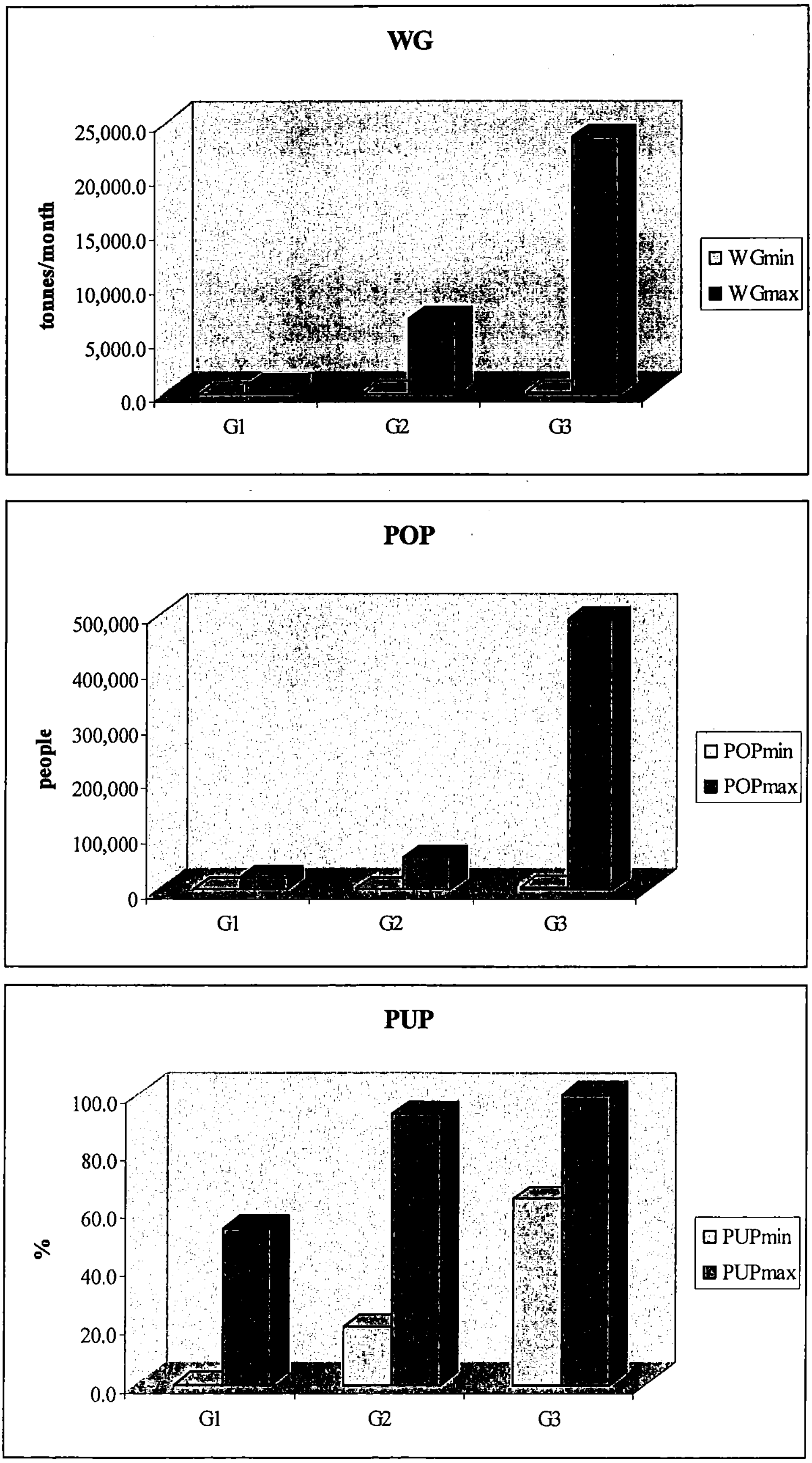
| GROUP 2 | WG (tonnes/month) | POP (people) | PUP (*100) | EDU (number) | LIB (number) | IND (people) |
|---|---|---|---|---|---|---|
| Lonquimay | 251.00 | 10,237 | 0.34 | 7.8 | 1 | 1,092 |
| Purén | 208.00 | 12,868 | 0.54 | 7.8 | 1 | 1,373 |
| Los Sauces | 40.86 | 7,581 | 0.42 | 7.8 | 1 | 809 |
| Ercilla | 28.00 | 9,041 | 0.34 | 7.8 | 1 | 965 |
| Lumaco | 9.30 | 11,405 | 0.28 | 7.8 | 1 | 1,217 |
| Traiguén | 290.00 | 19,534 | 0.67 | 7.9 | 8 | 3,403 |
| Victoria | 1,050.00 | 33,501 | 0.65 | 7.6 | 6 | 5,039 |
| Curacautín | 344.00 | 16,970 | 0.70 | 7.8 | 3 | 1,811 |
| Carahue | 450.00 | 25,696 | 0.39 | 6.2 | 2 | 4,444 |
| Nueva Imperial | 427.00 | 40,059 | 0.40 | 6.8 | 5 | 5,217 |
| Perquenco | 9.60 | 6,450 | 0.36 | 7.8 | 2 | 688 |
| Lautaro | 1,161.00 | 32,218 | 0.57 | 8.1 | 4 | 3,092 |
| Vilcún | 100.00 | 22,491 | 0.35 | 6.9 | 2 | 3,196 |
| Padre Las Casas | 1,312.40 | 58,795 | 0.53 | 8.1 | 4 | 10,388 |
| Teodoro Schmidt | 45.00 | 15,504 | 0.27 | 7.8 | 1 | 1,655 |
| Freire | 164.50 | 25,514 | 0.22 | 7.2 | 4 | 2,226 |
| Cunco | 50.00 | 18,703 | 0.36 | 7.8 | 3 | 1,996 |
| Pitrufquén | 141.00 | 21,988 | 0.52 | 8.1 | 6 | 2,637 |
| Gorbea | 143.00 | 15,222 | 0.56 | 7.3 | 4 | 3,110 |
| Loncoche | 307.00 | 23,037 | 0.60 | 7.8 | 3 | 3,677 |
| Villarrica | 1,414.00 | 45,531 | 0.63 | 8.1 | 6 | 2,870 |
| Pucón | 788.04 | 21,107 | 0.56 | 7.8 | 3 | 2,252 |
| Mariquina | 57.35 | 18,223 | 0.33 | 9.2 | 1 | 1,225 |
| Lanco | 104.90 | 15,107 | 0.62 | 9.2 | 1 | 1,015 |
| Panguipulli | 216.00 | 33,273 | 0.32 | 9.2 | 0 | 2,236 |
| Máfil | 60.00 | 7,213 | 0.42 | 9.2 | 1 | 485 |
| Los Lagos | 96.46 | 20,168 | 0.40 | 9.2 | 2 | 1,355 |
| Futrono | 71.50 | 14,981 | 0.31 | 9.2 | 0 | 1,007 |
| Corral | 72.00 | 5,463 | 0.62 | 9.2 | 1 | 367 |
| Paillaco | 92.04 | 19,237 | 0.43 | 9.2 | 1 | 1,293 |
| La Unión | 460.80 | 39,447 | 0.60 | 9.2 | 3 | 2,651 |
| RíoBueno | 384.00 | 32,627 | 0.40 | 9.2 | 2 | 2,193 |
| Puyehue | 400.40 | 11,368 | 0.30 | 9.2 | 1 | 764 |
| Río Negro | 90.00 | 14,732 | 0.40 | 9.2 | 2 | 990 |
| Purranque | 230.00 | 20,705 | 0.58 | 9.2 | 2 | 1,391 |
| Fresia | 192.00 | 12,804 | 0.40 | 9.2 | 1 | 860 |
| Frutillar | 60.00 | 15,525 | 0.38 | 9.2 | 0 | 1,043 |
| Puerto Varas | 529.80 | 32,912 | 0.68 | 9.2 | 1 | 2,212 |
| Llanquihue | 510.00 | 16,337 | 0.65 | 9.2 | 2 | 1,098 |
| Maullín | 144.00 | 15,580 | 0.35 | 9.2 | 2 | 1,047 |
| Calbuco | 187.50 | 31,070 | 0.32 | 9.2 | 2 | 2,088 |
| Ancud | 325.00 | 39,946 | 0.62 | 8.0 | 4 | 2,559 |
| Castro | 540.00 | 39,366 | 0.69 | 9.2 | 6 | 2,645 |
| Chonchi | 42.00 | 12,572 | 0.27 | 9.2 | 1 | 845 |
| Quellón | 600.00 | 21,823 | 0.50 | 9.2 | 1 | 1,467 |
| Chaitén | 20.00 | 7,182 | 0.45 | 9.2 | 1 | 483 |
| Futaleufú | 96.00 | 1,826 | 0.59 | 9.2 | 0 | 123 |
| Puerto Aysén | 700.00 | 22,353 | 0.80 | 7.8 | 6 | 0 |
| Chile Chico | 78.54 | 4,444 | 0.60 | 8.3 | 2 | 0 |
| Cochrane | 50.67 | 2,867 | 0.70 | 8.3 | 1 | 0 |
| Puerto Natales | 250.00 | 19,116 | 0.87 | 8.4 | 2 | 0 |
| Porvenir | 160.00 | 5,465 | 0.82 | 8.1 | 2 | 0 |
| Navarino | 288.00 | 2,262 | 0.85 | 8.7 | 1 | 0 |
| Tiltil | 507.00 | 14,755 | 0.48 | 8.2 | 1 | 461 |
| Lampa | 1,384.50 | 40,228 | 0.65 | 8.1 | 2 | 2,110 |
| Curacaví | 835.90 | 24,298 | 0.62 | 8.7 | 3 | 926 |
| Paine | 1,554.60 | 50,028 | 0.53 | 8.3 | 5 | 2,144 |
| Calera de Tango | 566.40 | 18,235 | 0.33 | 8.0 | 2 | 392 |
| Isla de Maipo | 887.58 | 25,798 | 0.67 | 8.1 | 3 | 737 |
| San José de Maipo | 460.20 | 13,376 | 0.68 | 9.7 | 2 | 564 |

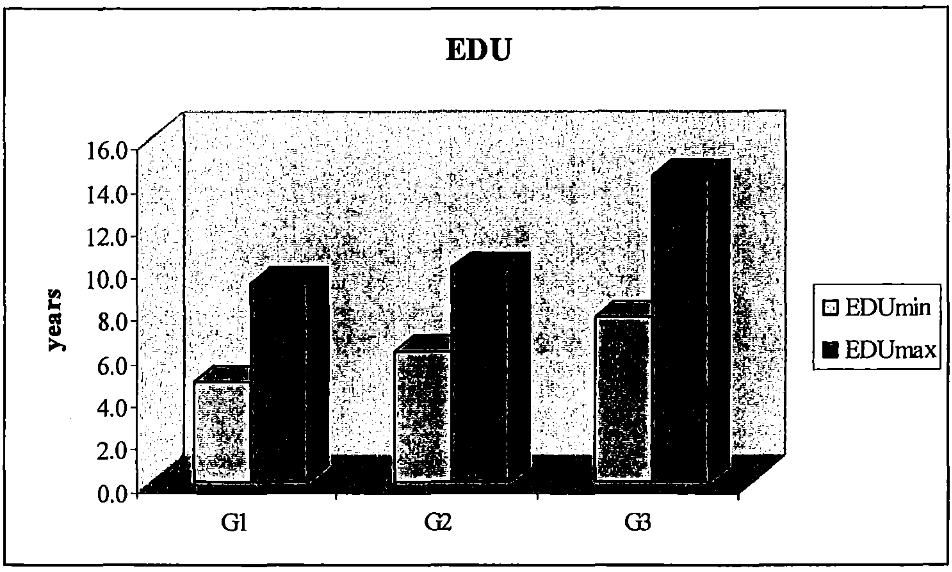
## Table A9.4: Data Group 3

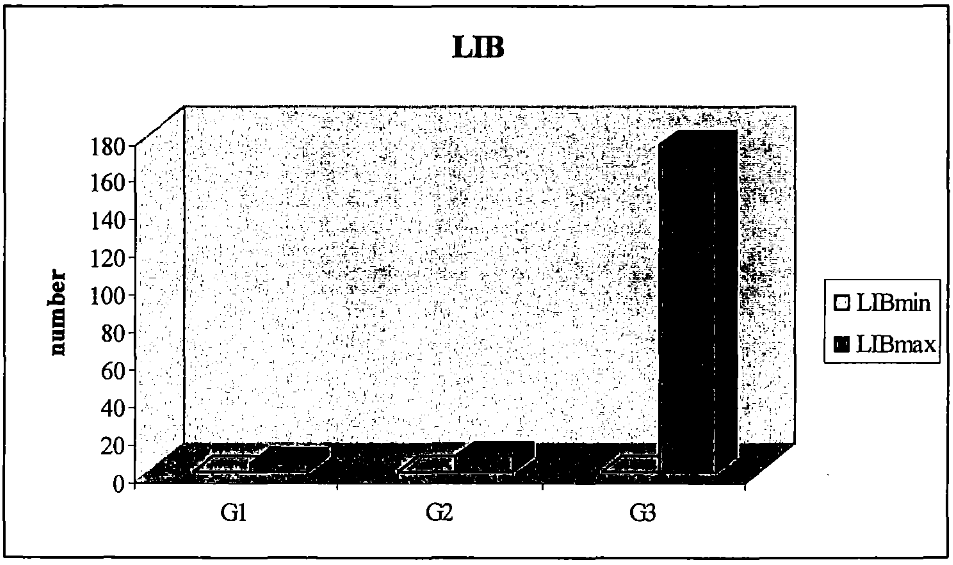
| GROUP 3 | WG (tonnes/month) | POP (people) | PUP (*100) | EDU (number) | LIB (number) | IND (people) |
|---|---|---|---|---|---|---|
| Arica | 3,000.00 | 185,268 | 0.95 | 10.1 | 41 | 11,511 |
| Iquique | 6,600.00 | 216,419 | 0.99 | 10.8 | 19 | 2,413 |
| Tocopilla | 750.00 | 23,986 | 0.98 | 9.4 | 8 | 2,868 |
| María Elena | 300.00 | 7,530 | 0.98 | 9.3 | 2 | 210 |
| Calama | 3,300.00 | 138,402 | 0.98 | 10.0 | 24 | 6,111 |
| Antofagasta | 18,331.00 | 296,905 | 0.99 | 10.9 | 39 | 1,501 |
| Taltal | 1,607.60 | 11,100 | 0.87 | 8.8 | 2 | 991 |
| Chañaral | 330.00 | 13,543 | 0.95 | 9.0 | 3 | 1,069 |
| Diego de Almagro | 288.00 | 18,589 | 0.94 | 9.9 | 4 | 2,440 |
| Caldera | 750.00 | 13,734 | 0.97 | 9.2 | 4 | 923 |
| Copiapó | 5,000.00 | 129,091 | 0.97 | 10.0 | 20 | 4,963 |
| Vallenar | 1,560.00 | 48,040 | 0.90 | 9.1 | 13 | 2,614 |
| La Serena | 5,751.84 | 160,148 | 0.90 | 11.0 | 32 | 5,755 |
| Coquimbo | 5,808.00 | 163,036 | 0.94 | 9.7 | 9 | 8,607 |
| Ovalle | 1,957.00 | 98,089 | 0.66 | 8.9 | 11 | 4,950 |
| Los Andes | 1,683.00 | 60,198 | 0.93 | 10.4 | 5 | 0 |
| San Felipe | 2,376.00 | 64,126 | 0.85 | 10.0 | 11 | 0 |
| Quintero | 587.00 | 21,174 | 0.91 | 9.8 | 3 | 1,266 |
| Calera | 854.10 | 49,503 | 0.97 | 9.1 | 7 | 2,383 |
| Quillota | 1,338.09 | 75,916 | 0.85 | 9.7 | 10 | 0 |
| Concón | 930.41 | 32,273 | 0.97 | 11.1 | 3 | 0 |
| Limache | 675.40 | 39,219 | 0.85 | 9.3 | 4 | 1,465 |
| Viña del Mar | 8,281.59 | 286,931 | 1.00 | 11.2 | 51 | 0 |
| Quilpué | 3,751.85 | 128,578 | 0.98 | 11.3 | 6 | 0 |
| Villa Alemana | 1,134.97 | 95,623 | 0.99 | 11.1 | 3 | 3,676 |
| Valparaiso | 7,540.00 | 275,982 | 1.00 | 10.2 | 60 | 19,166 |
| El Quisco | 1,134.23 | 9,467 | 0.94 | 8.3 | 1 | 673 |
| Cartagena | 2,021.75 | 16,875 | 0.87 | 9.0 | 1 | 651 |
| San Antonio | 3,472.11 | 87,205 | 0.96 | 9.2 | 8 | 4,652 |
| Isla de Pascua | 107.40 | 3,791 | 0.97 | 9.0 | 1 | 121 |
| Rancagua | 5,905.44 | 214,344 | 0.96 | 10.4 | 29 | 11,022 |
| Machali | 788.76 | 28,628 | 0.90 | 9.9 | 2 | 0 |
| San Fernando | 1,327.70 | 63,732 | 0.76 | 9.6 | 12 | 3,290 |
| Curicó | 3,267.60 | 119,585 | 0.77 | 8.9 | 11 | 3,109 |
| Talca | 5,400.00 | 201,797 | 0.94 | 10.1 | 23 | 4,085 |
| Linares | 2,408.66 | 83,249 | 0.77 | 9.1 | 7 | 5,710 |
| Chillán | 5,104.00 | 161,953 | 0.89 | 10.1 | 29 | 11,133 |
| Tomé | 1,260.00 | 52,440 | 0.84 | 9.0 | 3 | 6,009 |
| Penco | 1,116.00 | 46,016 | 0.98 | 10.1 | 2 | 0 |
| Concepción | 5,220.00 | 216,061 | 0.98 | 11.7 | 42 | 0 |
| Talcahuano | 6,048.00 | 250,348 | 0.99 | 10.3 | 10 | 20,153 |
| San Pedro de la Paz | 1,944.00 | 80,447 | 0.99 | 10.0 | 0 | 5,065 |
| Chiguayante | 1,962.00 | 81,302 | 1.00 | 10.1 | 1 | 3,270 |
| Coronel | 1,949.00 | 95,528 | 0.96 | 9.6 | 4 | 12,003 |
| Lota | 971.49 | 49,089 | 1.00 | 8.6 | 1 | 6,333 |
| Los Angeles | 1,126.93 | 166,556 | 0.67 | 9.1 | 27 | 7,710 |
| Curanilahue | 713.02 | 31,943 | 0.92 | 7.7 | 1 | 5,555 |
| Angol | 1,713.00 | 48,996 | 0.85 | 8.7 | 8 | 8,288 |
| Temuco | 5,487.60 | 245,347 | 0.94 | 11.4 | 40 | 7,495 |
| Valdivia | 3,392.00 | 140,559 | 0.93 | 10.1 | 15 | 12,209 |
| Osorno | 5,094.32 | 145,475 | 0.89 | 9.1 | 20 | 11,645 |
| Puerto Montt | 5,490.00 | 175,938 | 0.86 | 9.4 | 24 | 4,524 |
| Coihaique | 917.00 | 50,041 | 0.84 | 8.8 | 16 | 0 |
| Punta Arenas | 9,789.00 | 119,496 | 0.96 | 9.7 | 36 | 0 |
| Colina | 2,676.70 | 77,815 | 0.73 | 8.4 | 5 | 4,279 |
| Melipilla | 340.34 | 94,540 | 0.64 | 8.1 | 17 | 4,101 |
| Buin | 1,971.00 | 63,419 | 0.75 | 9.0 | 5 | 2,041 |
| San Bernardo | 8,489.00 | 246,762 | 0.95 | 9.4 | 19 | 9,194 |
| Padre Hurtado | 1,204.80 | 38,768 | 0.88 | 9.1 | 4 | 1,630 |
| Peñaflor | 2,070.60 | 66,619 | 0.93 | 9.6 | 5 | 3,368 |
| El Monte | 95.25 | 26,459 | 0.82 | 8.5 | 2 | 3,643 |
| Talagante | 2,057.90 | 59,805 | 0.83 | 9.2 | 16 | 2,882 |
| Puente Alto | 15,318.60 | 492,915 | 1.00 | 10.3 | 27 | 16,768 |
| Lo Barnechea | 2,571.40 | 74,749 | 0.93 | 11.3 | 13 | 1,652 |
| Vitacura | 2,804.10 | 81,499 | 1.00 | 14.2 | 19 | 0 |
| Las Condes | 8,596.90 | 249,893 | 1.00 | 14.0 | 47 | 1,362 |
| La Reina | 3,329.30 | 96,762 | 1.00 | 13.4 | 16 | 1,376 |
| Peñalolén | 23,650.60 | 216,060 | 1.00 | 9.9 | 6 | 8,839 |
| La Florida | 11,364.00 | 365,674 | 1.00 | 11.5 | 30 | 4,065 |
| Huechuraba | 2,548.00 | 74,070 | 0.99 | 9.4 | 2 | 3,803 |
| Recoleta | 5,098.60 | 148,220 | 1.00 | 9.8 | 23 | 4,445 |
| Providencia | 4,158.70 | 120,874 | 1.00 | 14.3 | 89 | 0 |
| Ñuñoa | 5,625.10 | 163,511 | 1.00 | 13.4 | 62 | 3,360 |
| Macul | 7,368.86 | 112,535 | 1.00 | 11.0 | 11 | 2,774 |
| Conchalí | 4,583.80 | 133,256 | 1.00 | 9.8 | 6 | 4,305 |
| Independencia | 2,252.90 | 65,479 | 1.00 | 10.4 | 22 | 887 |
| Santiago | 6,908.20 | 200,792 | 1.00 | 11.8 | 174 | 854 |
| San Joaquín | 3,359.20 | 97,625 | 1.00 | 9.8 | 13 | 2,151 |
| La Granja | 4,118.40 | 132,520 | 1.00 | 9.5 | 7 | 6,646 |
| San Ramón | 2,949.60 | 94,906 | 1.00 | 9.0 | 9 | 3,658 |
| La Pintana | 5,907.60 | 190,085 | 1.00 | 8.7 | 4 | 22,829 |
| San Miguel | 2,713.10 | 78,872 | 1.00 | 11.6 | 28 | 857 |
| La Cisterna | 2,928.90 | 85,118 | 1.00 | 11.0 | 19 | 960 |
| El Bosque | 5,457.00 | 175,594 | 1.00 | 9.6 | 9 | 13,004 |
| Pedro Aguirre Cerda | 8,598.80 | 114,560 | 1.00 | 9.1 | 7 | 0 |
| Lo Espejo | 3,505.80 | 112,800 | 1.00 | 9.0 | 4 | 11,148 |
| Quilicura | 4,352.40 | 126,518 | 0.97 | 9.9 | 2 | 3,708 |
| Renca | 4,592.90 | 133,518 | 1.00 | 8.8 | 8 | 5,095 |
| Quinta Normal | 3,578.90 | 104,012 | 1.00 | 10.0 | 17 | 3,591 |
| Cerro Navia | 5,102.50 | 148,312 | 1.00 | 8.7 | 7 | 7,430 |
| Lo Prado | 3,589.30 | 104,316 | 1.00 | 9.9 | 4 | 3,297 |
| Estación Central | 9,787.20 | 130,394 | 1.00 | 10.0 | 21 | 6,559 |
| Cerrillos | 5,397.20 | 71,906 | 1.00 | 10.2 | 5 | 1,325 |
| Pudahuel | 6,731.40 | 195,653 | 0.97 | 9.9 | 8 | 7,588 |
| Maipú | 16,113.50 | 468,390 | 0.99 | 11.0 | 21 | 7,597 |

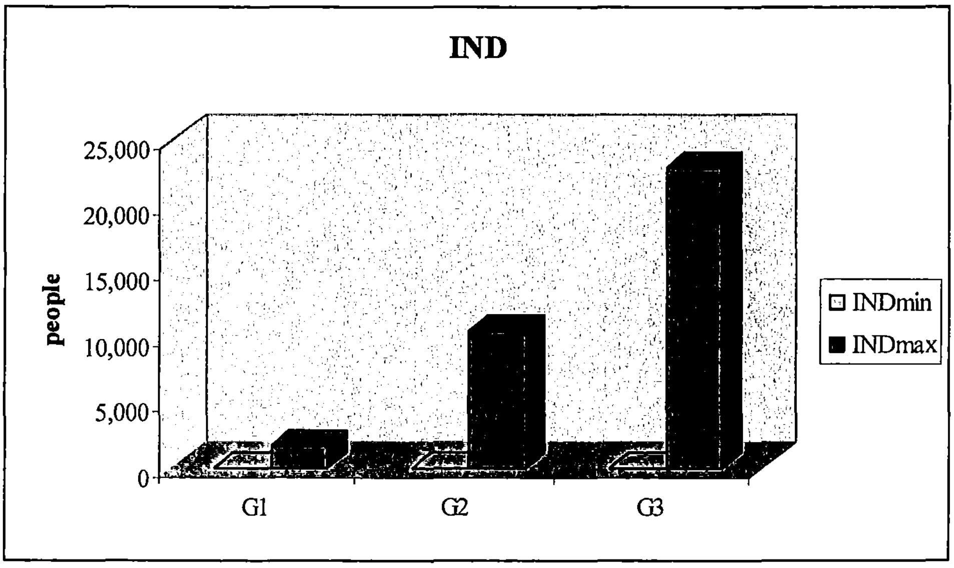
# APPENDIX 10

Figure A10.1: Minimum and Maximum values for the Explanatory and Explained Variables for the 342 communes





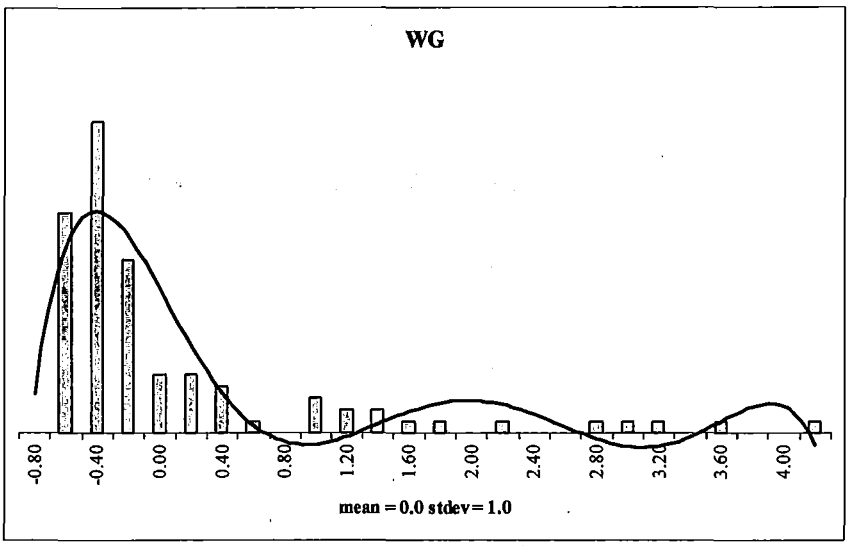



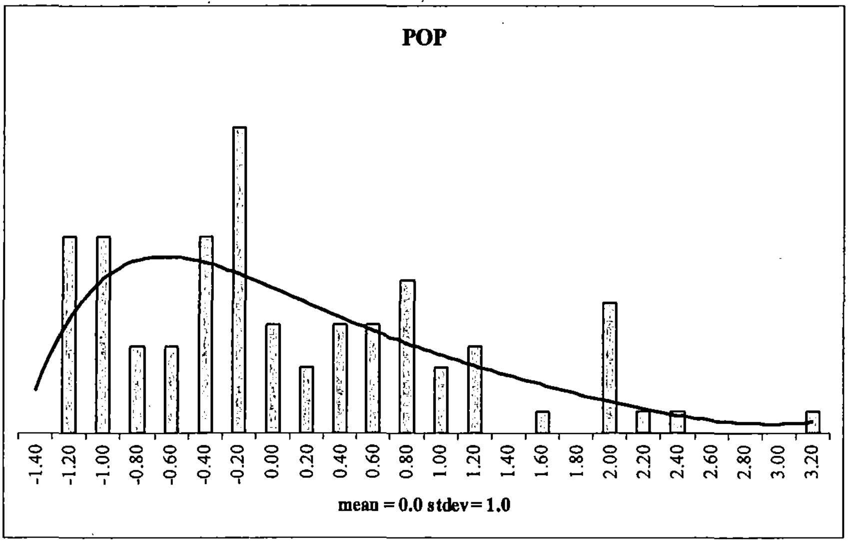

Appendix 10 (cont.)

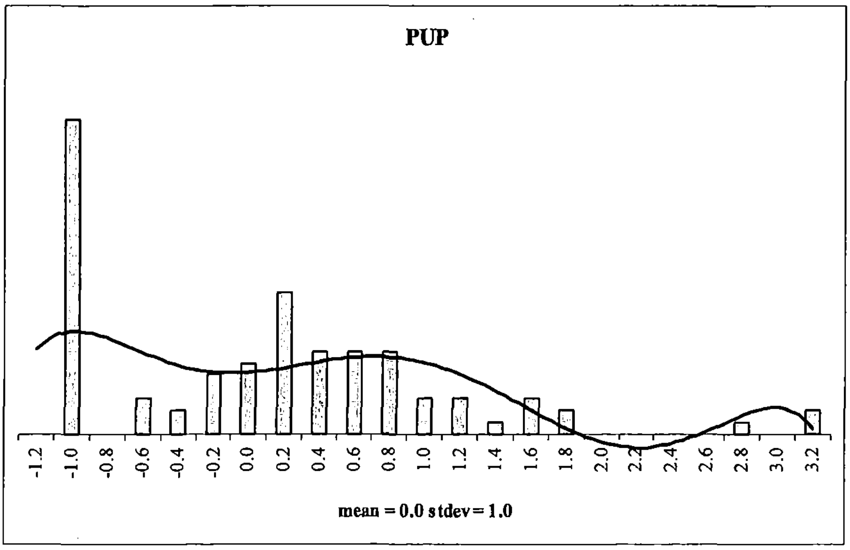
# APPENDIX 11

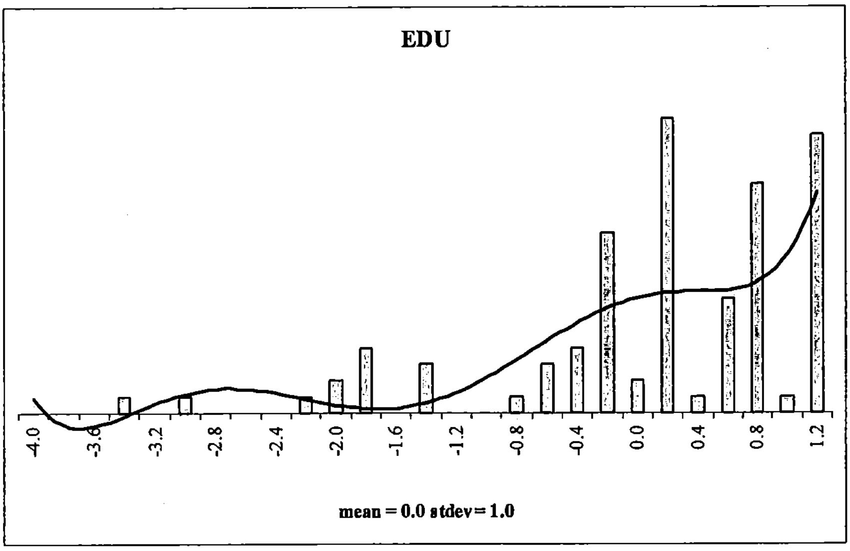
Mean and Standard Deviation for the Explanatory and Explained Variables for the 342 Communes

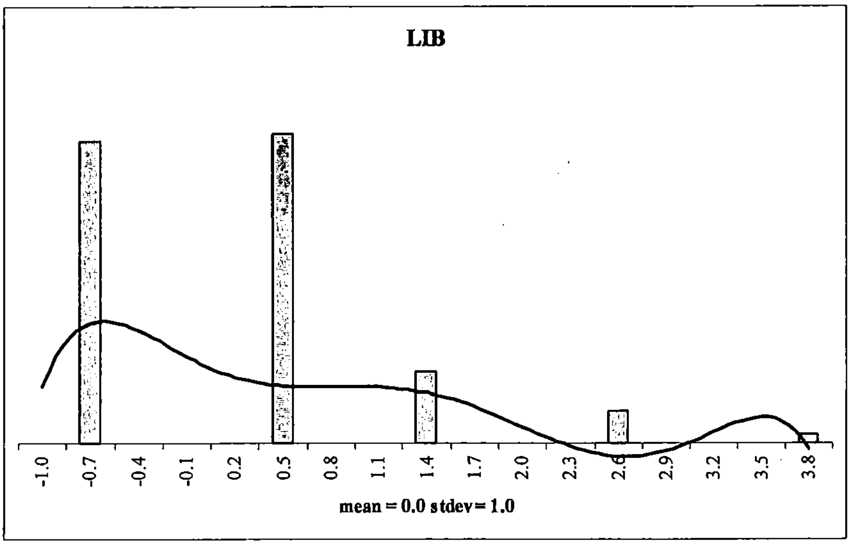
Figure A11.1: Mean and Standard Deviation for the Explanatory and Explained Variables for the communes of Group 1

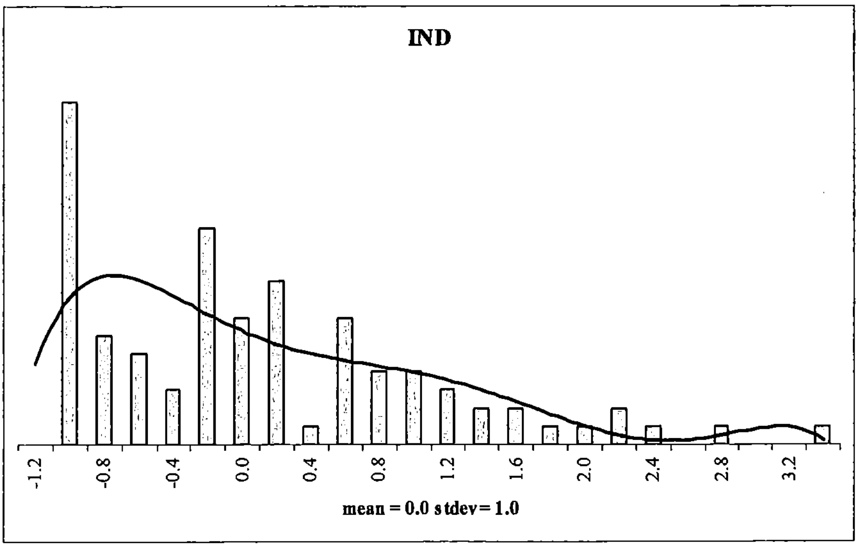


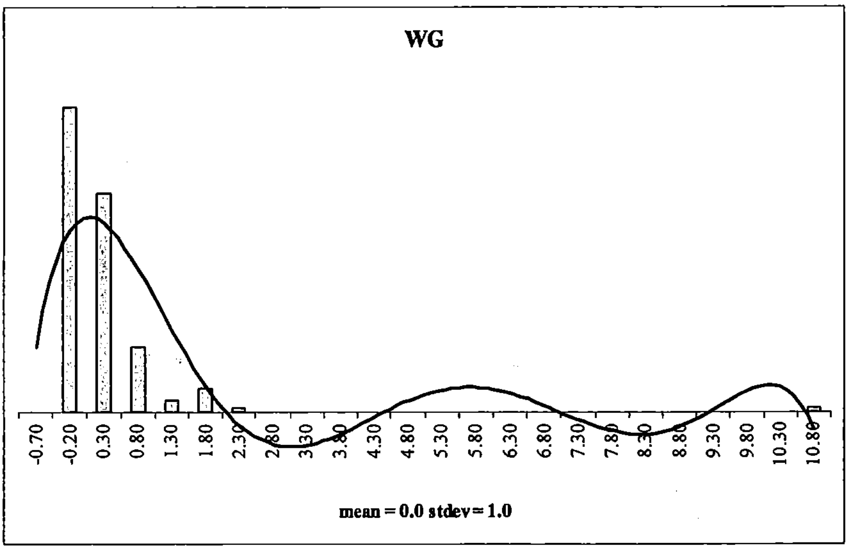


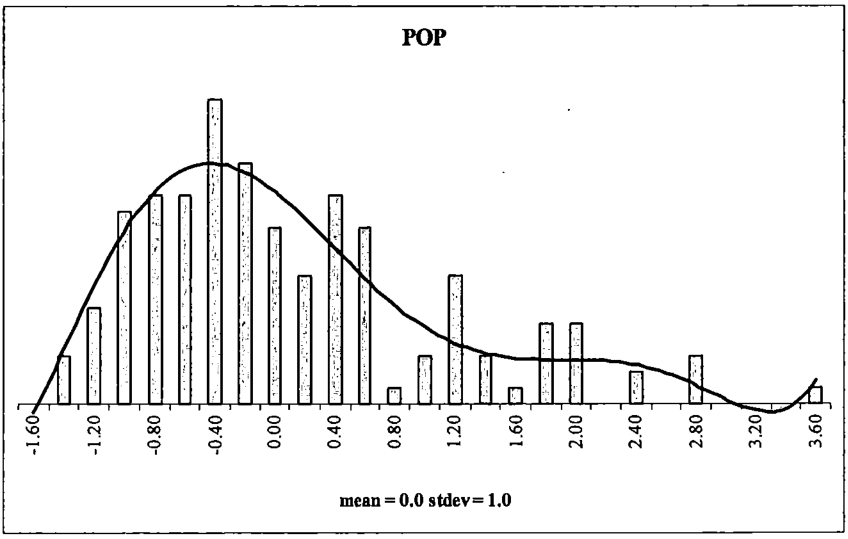



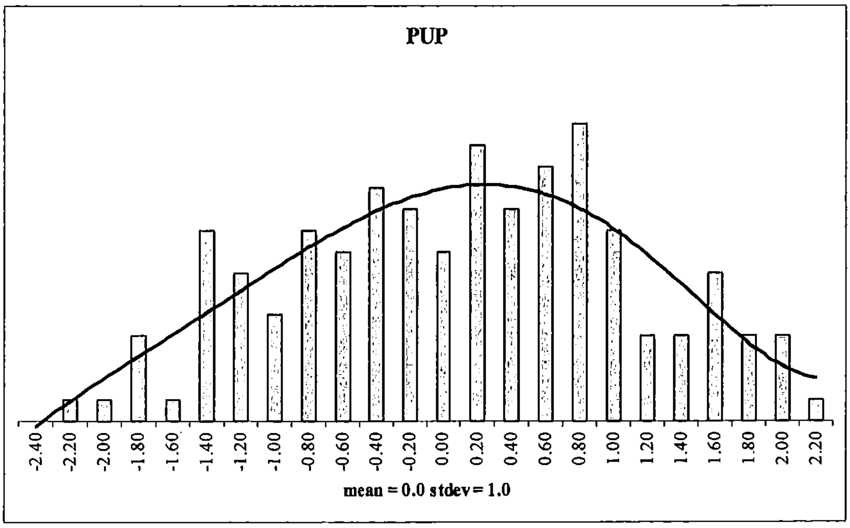




Appendix 11 (cont.)

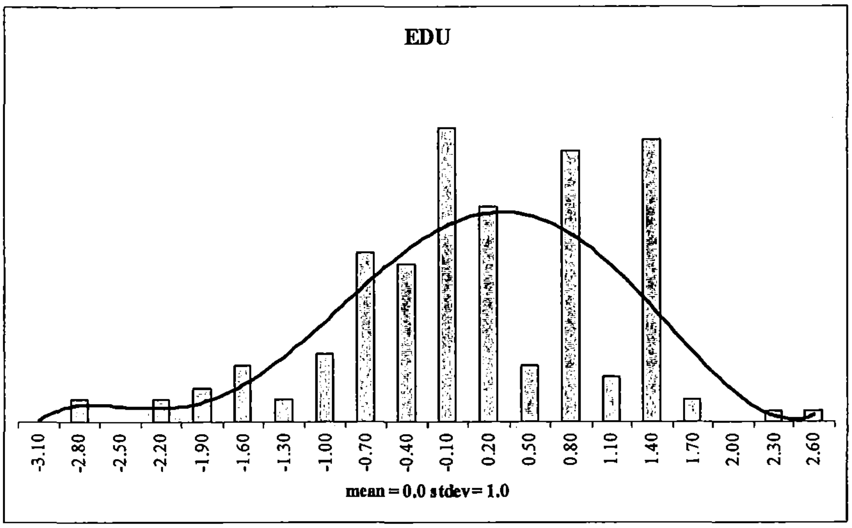
Figure A11.2: Mean and Standard Deviation for the Explanatory and Explained Variables for the communes of Group 2

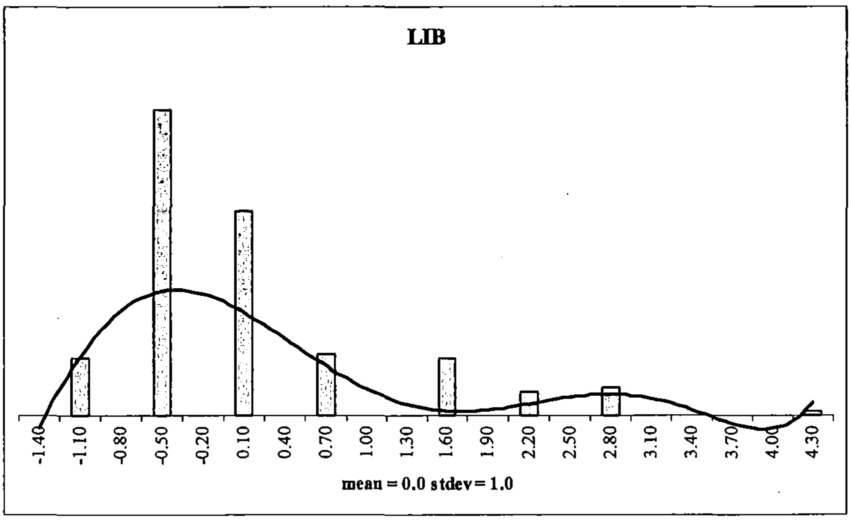


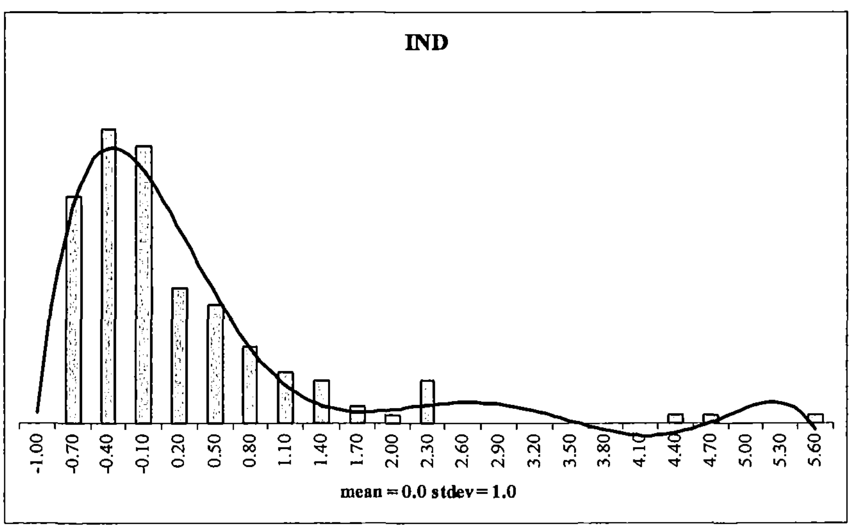




Appendix 11 (cont.)

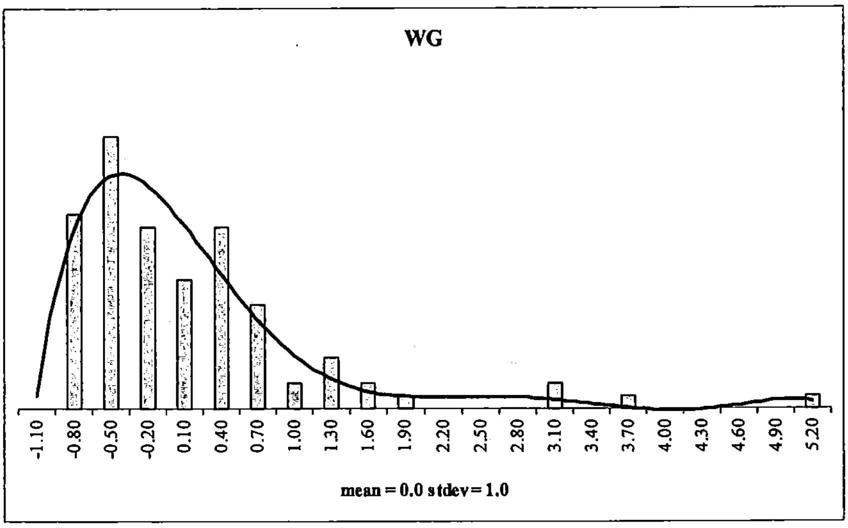


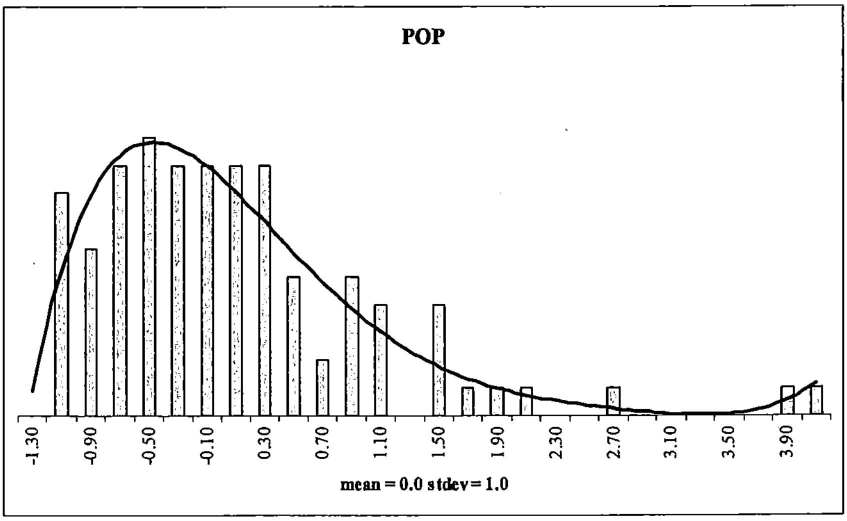



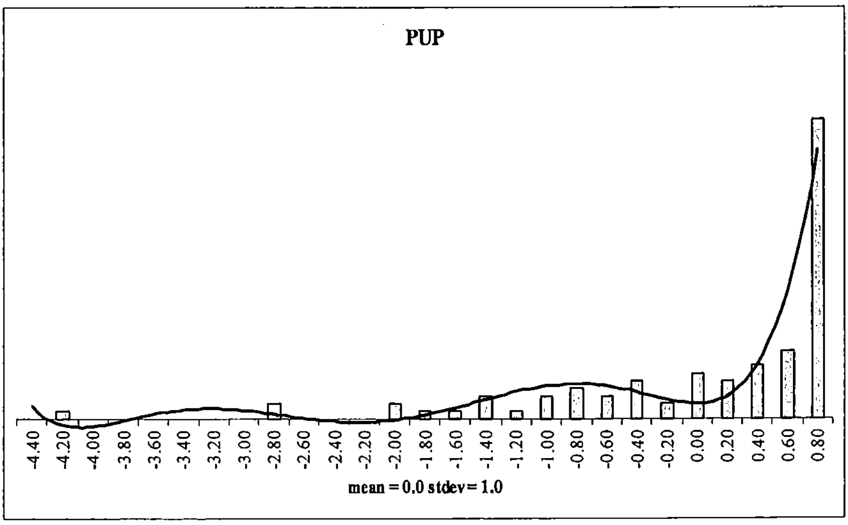




Appendix 11 (cont.)

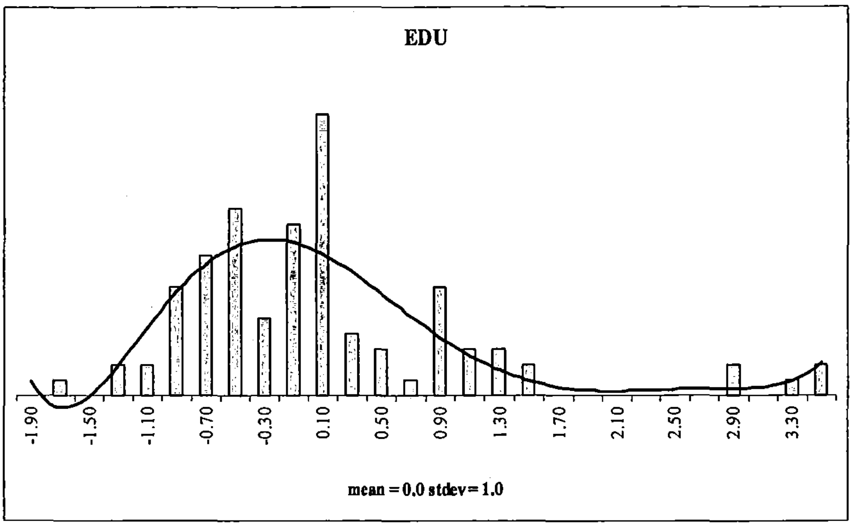
Figure A11.3: Mean and Standard Deviation for the Explanatory and Explained Variables for the communes of Group 3

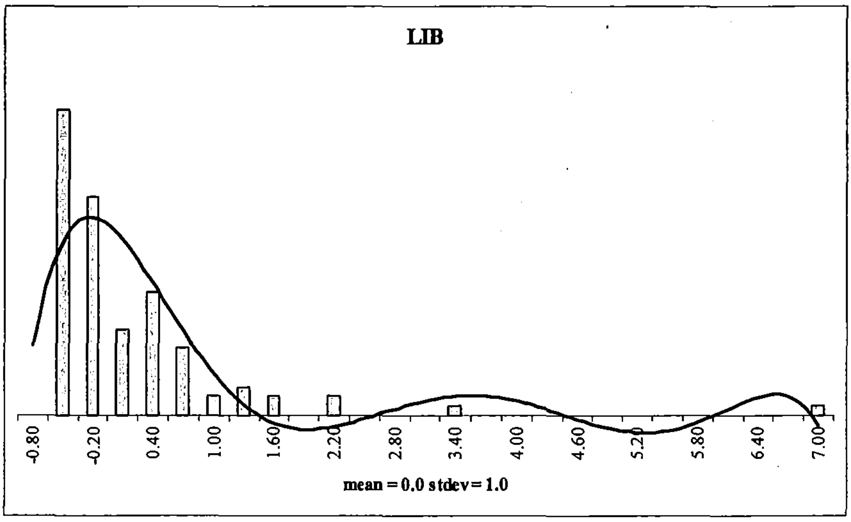


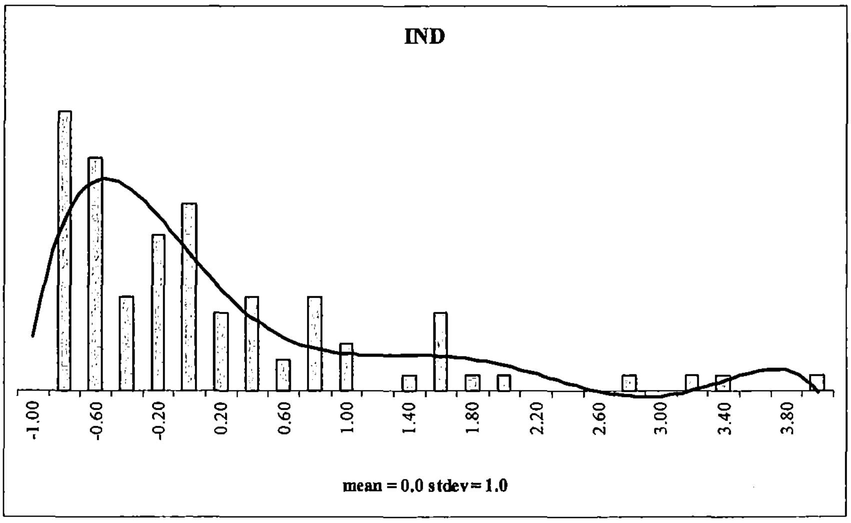




Appendix 11 (cont.)




Appendix 11 (cont.)

# APPENDIX 12

## Table A12.1: Level of Representativeness of Every Commune per Group

| GROUP 1 | | GROUP 2 | | | | GROUP 3 | |
|---|---|---|---|---|---|---|---|
| **Marchihue** | 44.0% | **Olmué** | 75.0% | Florida | 53.8% | **Coronel** | 76.8% |
| **Paredones** | 44.0% | **Pichilemu** | 75.0% | Teodoro Schmidt | 53.8% | Macul | 75.8% |
| **Cobquecura** | 44.0% | **Santa Juana** | 75.0% | Chonchi | 53.8% | Independencia | 75.8% |
| **Ninhue** | 44.0% | **Lanco** | 75.0% | Tiltil | 53.8% | San Joaquín | 75.8% |
| **Ránquil** | 44.0% | Salamanca | 73.7% | Punitaqui | 53.2% | La Reina | 74.7% |
| San Pedro de Atacama | 42.9% | Cabildo | 73.7% | Catemu | 53.2% | La Granja | 74.7% |
| Canela | 41.8% | Yumbel | 73.7% | Gorbea | 53.2% | **San Ramón** | 74.7% |
| Pencahue | 41.8% | Carahue | 73.7% | Máfil | 53.2% | La Cisterna | 74.7% |
| La Estrella | 40.7% | Quellón | 73.7% | Nogales | 52.6% | Lo Espejo | 74.7% |
| Lago Ranco | 40.7% | Los Lagos | 73.1% | Cabrero | 52.6% | San Antonio | 73.7% |
| Hualaihué | 40.7% | Freire | 72.4% | Los Alamos | 52.6% | Lo Barnechea | 73.7% |
| **María Pinto** | 40.7% | San José de Maipo | 72.4% | Lumaco | 52.6% | Renca | 73.7% |
| Yerbas Buenas | 39.6% | Coelemu | 71.8% | Perquenco | 52.6% | Coquimbo | 72.6% |
| Contulmo | 38.5% | Cunco | 71.8% | Loncoche | 52.6% | Puerto Montt | 72.6% |
| Ñiquén | 37.4% | Maullín | 71.2% | Coihueco | 51.9% | Talagante | 72.6% |
| Tirúa | 37.4% | Los Vilos | 70.5% | Santa Cruz | 51.3% | Conchalí | 72.6% |
| Saavedra | 37.4% | Hualqui | 70.5% | Licantén | 51.3% | San Miguel | 72.6% |
| San Pablo | 37.4% | Negrete | 70.5% | Los Sauces | 51.3% | Cerro Navia | 72.6% |
| Puerto Octay | 37.4% | Renaico | 70.5% | Nueva Imperial | 51.3% | Lo Prado | 72.6% |
| Petorca | 36.3% | Vilcún | 70.5% | Coinco | 50.6% | Pudahuel | 72.6% |
| Curepto | 36.3% | Purranque | 70.5% | La Unión | 50.6% | Villa Alemana | 71.6% |
| San Fabián | 36.3% | RíoBueno | 69.9% | Puyehue | 50.6% | Los Angeles | 71.6% |
| San Nicolás | 36.3% | Río Negro | 69.9% | Pica | 50.0% | Peñaflor | 71.6% |
| Quilaco | 36.3% | Calbuco | 69.9% | Rauco | 49.4% | Providencia | 71.6% |
| Galvarino | 36.3% | **Puerto Aysén** | 69.9% | Lebu | 49.4% | Calera | 70.5% |
| Los Muermos | 36.3% | Yungay | 69.2% | **Puerto Natales** | 49.4% | Angol | 70.5% |
| Quemchi | 36.3% | Laja | 68.6% | Puchuncaví | 48.1% | Peñalolén | 70.5% |
| Quinchao | 36.3% | Santa María | 67.3% | Parral | 48.1% | Quinta Normal | 70.5% |
| Toltén | 35.2% | Hijuelas | 67.3% | San Clemente | 46.8% | Vallenar | 69.5% |
| Navidad | 34.1% | Santa Bárbara | 67.3% | Lautaro | 46.8% | San Fernando | 69.5% |
| Retiro | 34.1% | **Purén** | 67.3% | Corral | 46.8% | Iquique | 68.4% |
| San Ignacio | 34.1% | Monte Patria | 66.7% | Chanco | 46.2% | Linares | 68.4% |
| Alhué | 34.1% | Vicuña | 66.0% | Lonquimay | 46.2% | Calama | 67.4% |
| El Carmen | 31.9% | Llaillay | 66.0% | Ancud | 46.2% | Copiapó | 67.4% |
| Melipeuco | 31.9% | Olivar | 66.0% | Malloa | 45.5% | Talca | 67.4% |
| La Higuera | 30.8% | Hualañé | 66.0% | Molina | 45.5% | Valdivia | 67.4% |
| Pelluhue | 30.8% | Chillán Viejo | 66.0% | Cauquenes | 45.5% | Estación Central | 67.4% |
| Antuco | 30.8% | Paillaco | 66.0% | Ercilla | 45.5% | Antofagasta | 66.3% |
| Cisnes | 30.8% | Curacaví | 66.0% | Freirina | 44.9% | Lota | 66.3% |
| Alto del Carmen | 29.7% | Bulnes | 65.4% | Paine | 44.2% | Osorno | 66.3% |
| Calle Larga | 29.7% | Puerto Varas | 65.4% | Teno | 43.6% | San Bernardo | 66.3% |
| Cochamó | 29.7% | Isla de Maipo | 65.4% | La Ligua | 42.9% | Huechuraba | 66.3% |
| Puqueldón | 29.7% | San Javier | 64.7% | Mulchén | 41.7% | Recoleta | 66.3% |
| Maule | 28.6% | Pinto | 64.7% | Sagrada Familia | 41.0% | La Pintana | 66.3% |
| San Pedro | 28.6% | Calera de Tango | 64.7% | Colbún | 41.0% | El Bosque | 66.3% |
| Litueche | 27.5% | Mejillones | 64.1% | Pitrufquén | 40.4% | Cerrillos | 66.3% |
| Portezuelo | 27.5% | Tucapel | 64.1% | El Tabo | 39.1% | Tomé | 65.3% |
| Queilén | 27.5% | Mariquina | 64.1% | Huasco | 37.8% | La Serena | 64.2% |
| **Pichidegua** | 26.4% | Llanquihue | 63.5% | Nacimiento | 37.8% | Curicó | 64.2% |
| Lolol | 26.4% | Andacollo | 62.8% | Longaví | 37.2% | Quilicura | 64.2% |
| Dalcahue | 26.4% | Graneros | 62.2% | Porvenir | 37.2% | Ovalle | 63.2% |
| Romeral | 25.3% | Quillón | 62.2% | Villarrica | 35.9% | Chiguayante | 60.0% |
| Requínoa | 24.2% | Pozo Almonte | 61.5% | Illapel | 34.6% | La Florida | 57.9% |
| Placilla | 24.2% | Combarbalá | 61.5% | Padre Las Casas | 34.6% | Chillán | 56.8% |
| Río Claro | 24.2% | San Esteban | 61.5% | La Cruz | 34.0% | Colina | 56.8% |
| Trehuaco | 24.2% | Arauco | 61.5% | Rengo | 34.0% | Melipilla | 56.8% |
| Pelarco | 23.1% | Lampa | 61.5% | Empedrado | 33.3% | Talcahuano | 55.8% |
| Curarrehue | 23.1% | Rinconada | 60.9% | Castro | 32.1% | Las Condes | 55.8% |
| San Juan de la Costa | 23.1% | Cañete | 60.9% | Victoria | 30.8% | Curanilahue | 54.7% |
| Palmilla | 22.0% | Las Cabras | 60.3% | San Rosendo | 30.1% | Maipú | 53.7% |
| Vichuquén | 22.0% | Peralillo | 60.3% | Traiguén | 26.3% | Rancagua | 52.6% |
| Sierra Gorda | 20.9% | Quilleco | 60.3% | Papudo | 25.6% | Arica | 49.5% |
| Río Ibáñez | 15.4% | **Peumo** | 59.0% | Constitución | 21.2% | Temuco | 49.5% |
| Pirque | 15.4% | Chimbarongo | 59.0% | Chile Chico | 20.5% | Buin | 48.4% |
| Pumanque | 13.2% | Collipulli | 59.0% | Frutillar | 14.7% | Limache | 46.3% |
| Paihuano | 12.1% | Pucón | 59.0% | Casablanca | 13.5% | Padre Hurtado | 46.3% |
| Coltauco | 12.1% | Mostazal | 58.3% | Panguipulli | 13.5% | El Monte | 44.2% |
| Curaco De Vélez | 12.1% | Chépica | 58.3% | Futrono | 10.9% | Puente Alto | 43.2% |
| Putre | 11.0% | Fresia | 58.3% | San Vicente | 7.7% | Tocopilla | 41.1% |
| Huara | 11.0% | San Carlos | 57.7% | Cochrane | 7.7% | San Pedro de la Paz | 41.1% |
| Colchane | 11.0% | Doñihue | 56.4% | Nancagua | 7.1% | Ñuñoa | 40.0% |
| Zapallar | 11.0% | Curacautín | 56.4% | Navarino | 7.1% | Viña del Mar | 35.8% |
| Camiña | 9.9% | Tierra Amarilla | 55.8% | Pemuco | 6.4% | Vitacura | 34.7% |
| Palena | 9.9% | Chaitén | 55.8% | Villa Alegre | 5.1% | Quintero | 32.6% |
| RíoHurtado | 8.8% | Quinta de Tilcoco | 54.5% | Panquehue | 4.5% | Diego de Almagro | 30.5% |
| Santo Domingo | 7.7% | Quirihue | 54.5% | San Rafael | 4.5% | Concepción | 30.5% |
| Guaitecas | 7.7% | Putaendo | 53.8% | Algarrobo | 2.6% | Punta Arenas | 29.5% |
| Lago Verde | 7.7% | Codegua | 53.8% | Futaleufú | 1.3% | Santiago | 26.3% |
| Torres del Paine | 7.7% | | | | | Valparaíso | 24.2% |
| Camarones | 5.5% | | | | | Chañaral | 18.9% |
| Tortel | 5.5% | | | | | Caldera | 18.9% |
| O'Higgins | 5.5% | | | | | Cartagena | 16.8% |
| Laguna Blanca | 5.5% | | | | | Taltal | 14.7% |
| San Gregorio | 5.5% | | | | | Coihaique | 12.6% |
| Primavera | 5.5% | | | | | San Felipe | 11.6% |
| Timaukel | 4.4% | | | | | Concón | 11.6% |
| General Lagos | 3.3% | | | | | Quilpué | 11.6% |
| Río Verde | 3.3% | | | | | El Quisco | 11.6% |
| Ollagüe | 2.2% | | | | | María Elena | 10.5% |
| Juan Fernández | 2.2% | | | | | Quillota | 10.5% |
| Antártica | 1.1% | | | | | Pedro Aguirre Cerda | 10.5% |
| | | | | | | Los Andes | 9.5% |
| | | | | | | Machalí | 9.5% |
| | | | | | | Penco | 9.5% |
| | | | | | | Isla de Pascua | 2.1% |

Total number of communes covered per group and the communes represented by the most representative communes

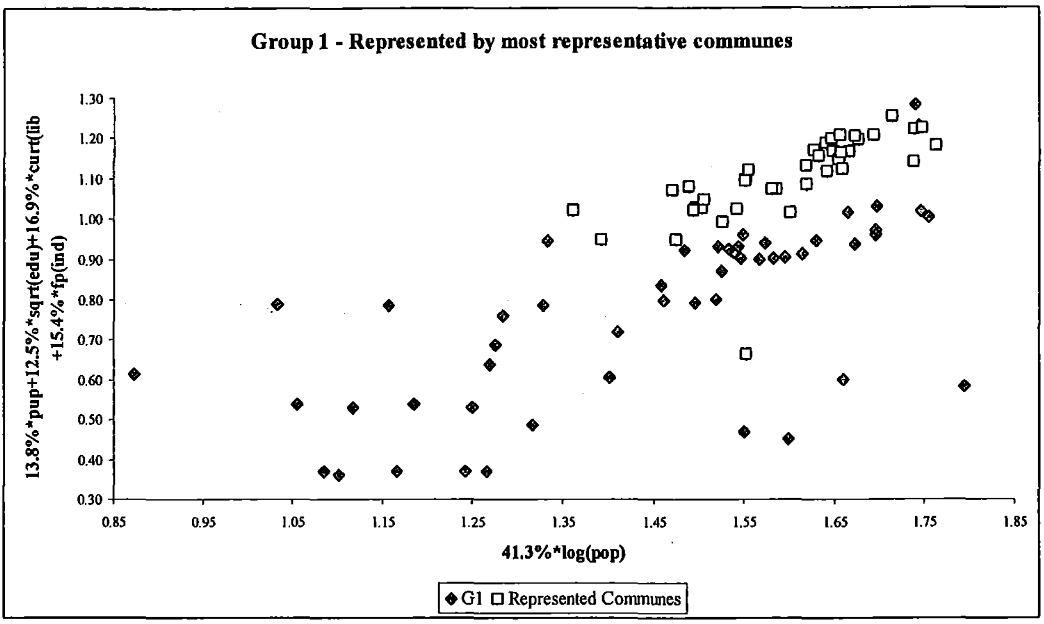



Figure A12.1: Group 1 – The total 91 communes and the 40 represented communes

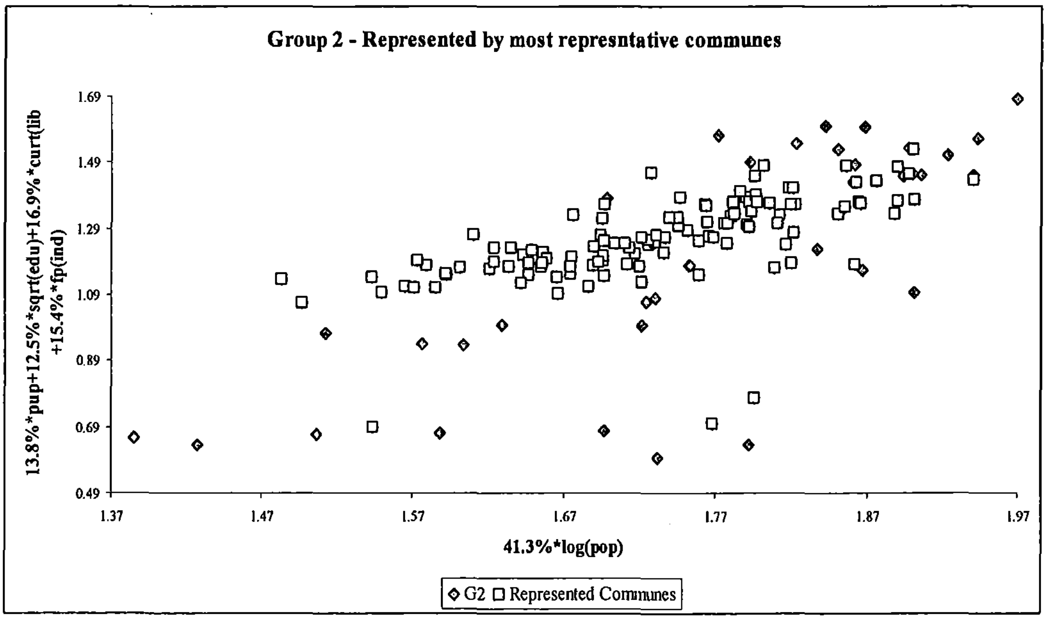



Figure A12.2: Group 2 – The total 156 communes and the 117 represented communes

Appendix 12 (cont.)

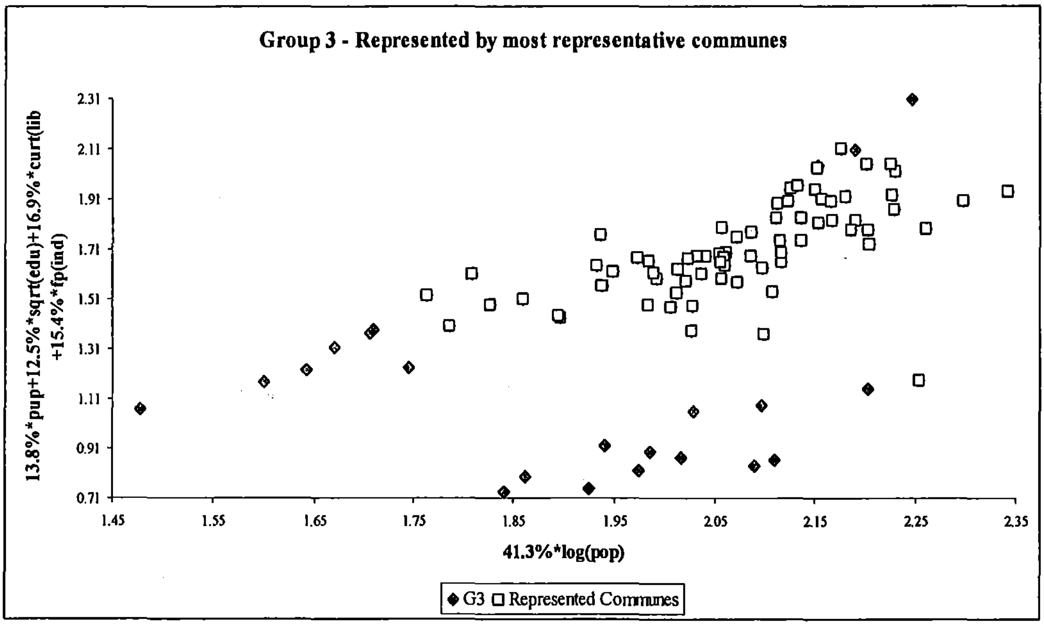



Figure A12.3: Group 3 – The total 95 communes and the 73 represented communes

Appendix 12 (cont.)

# APPENDIX 13

Calculations to determine Communes Represented per Group

Table A13.1: Calculations to determine Communes Represented per Group

| | Representative Commune | (A) Total Number of Communes | (B) Representativeness (±15% Range) | (C = A x B) Represented Communes | (D) Data Availability | (E = C x D) | Final Communes Represented |
|---|---|---|---|---|---|---|---|
| G1 | María Pinto | 91 | 40.7% | 37 | 94.4% | 35(1) | 36(8) |
| | *Pichidegua* | | 26.4% | 24 | 5.6% | 1(2) | |
| G2 | *Puerto Aysén* | 156 | 69.9% | 109 | 13.3% | 15(3) | 60(9) |
| | *Purén* | | 67.3% | 105 | 50.0% | 52(4) | |
| | *Peumo* | | 59.0% | 92 | 25.0% | 23(5) | |
| | *Puerto Natales* | | 49.4% | 77 | 11.1% | 9(6) | |
| G3 | *San Ramón* | 95 | 74.7% | 71 | 100.0% | 71(7) | 71(10) |

Due to the Data Availability factor (D), the numbers of Represented Communes (C) were reduced (E). Then, the level of representativeness for Group 1 and 2 communes was adjusted until the required numbers of communes were found.

(1) *María Pinto*'s was reduced to 12.5%;

(2) *Pichidegua*'s to 0%;

(3) *Puerto Aysen*'s to 3.3%;

(4) *Purén*'s to 7.3%;

(5) *Peumo*'s to 3.8%;

(6) *Puerto Natales*' to 4%.

(7) As San Ramón was the only representative communes in Group 3, the level of representativeness was not altered.

(8) The final communes represented in Group 1 are the 35 represented by *María Pinto* and the one represented by *Pichidegua* (itself). As *María Pinto* does not represent *Pichidegua*, both figures are added.

(9) In Group 2, two, three or the four representative communes represent same communes. For instance, the four representative communes represent *Freirina* but this should be considered only once. This is why the sum is not straightforward.

Calculations Details

$$\alpha \equiv 41.3\% * \frac{\log(POP)}{\max(\log(POP))}$$

$$\beta \equiv 13.8\% PUP + 12.5\% * \frac{\sqrt{EDU}}{\max(\sqrt{EDU})} + 16.9\% * \frac{\sqrt[3]{LIB}}{\max(\sqrt[3]{LIB})} + 15.4\% * \frac{\sqrt[5]{IND}}{\max(\sqrt[5]{IND})}$$

Table A13.2: Calculations to determine Communes Represented in Group 1

| **Group 1** | | | ***María Pinto (±12.5%)*** | | ***Pichidegua (±0.0%)*** | |
|---|---|---|---|---|---|---|
| | **α** | **β** | ***[0.33385-0.42924] α = 0.38155*** | ***[0.32667-0.42000] β = 0.37334*** | ***[0.40835-0.40835] α = 0.40835*** | ***[0.29300-0.29300] β = 0.29300*** |
| General Lagos | 0.29191 | 0.17120 | | | | |
| Putre | 0.31325 | 0.41400 | | | | |
| Camarones | 0.29332 | 0.18662 | | | | |
| Huara | 0.32454 | 0.19683 | | | | |
| Camiña | 0.29514 | 0.20343 | | | | |
| Colchane | 0.30576 | 0.20644 | | | | |
| Ollagüe | 0.23783 | 0.28506 | | | | |
| Sierra Gorda | 0.32049 | 0.33919 | | | | |
| San Pedro de Atacama | 0.35129 | 0.38587 | **X** | | | |
| Alto del Carmen | 0.35020 | 0.31153 | | | | |
| La Higuera | 0.33935 | 0.34445 | **X** | | | |
| RíoHurtado | 0.34961 | 0.21233 | | | | |
| Paihuano | 0.34403 | 0.21492 | | | | |
| Canela | 0.37751 | 0.38736 | **X** | | | |
| Petorca | 0.37778 | 0.40726 | **X** | | | |
| Zapallar | 0.35666 | 0.23162 | | | | |
| Calle Larga | 0.38175 | 0.29616 | | | | |

Appendix 13 (cont.)

| | | | | |
|---|---|---|---|---|
| Santo Domingo | 0.36783 | 0.20763 | | |
| Juan Fernández | 0.26624 | 0.31667 | | |
| Navidad | 0.35489 | 0.35020 | X | |
| Litueche | 0.35567 | 0.28793 | | |
| Coltauco | 0.40014 | 0.48015 | | |
| La Estrella | 0.34456 | 0.37194 | X | |
| Marchihue | 0.36486 | 0.38154 | X | |
| Paredones | 0.36360 | 0.38195 | X | |
| Pichidegua | 0.40385 | 0.29300 | | X |
| Requínoa | 0.41300 | 0.28900 | | |
| Pumanque | 0.33613 | 0.21627 | | |
| Lolol | 0.36036 | 0.27571 | | |
| Palmilla | 0.38483 | 0.26814 | | |
| Placilla | 0.37135 | 0.27065 | | |
| Vichuquén | 0.35085 | 0.26176 | | |
| Romeral | 0.39004 | 0.28577 | | |
| Curepto | 0.38338 | 0.41615 | X | |
| Pencahue | 0.37254 | 0.37555 | X | |
| Maule | 0.40166 | 0.30862 | | |
| Río Claro | 0.39001 | 0.27465 | | |
| Pelarco | 0.36697 | 0.26670 | | |
| Pelluhue | 0.36183 | 0.31265 | | |
| Retiro | 0.40552 | 0.39759 | X | |
| Yerbas Buenas | 0.39990 | 0.37232 | X | |
| Cobquecura | 0.35686 | 0.38147 | X | |
| Ninhue | 0.35723 | 0.37992 | X | |
| Ñiquén | 0.38564 | 0.40426 | X | |
| San Fabián | 0.33851 | 0.39023 | X | |
| Trehuaco | 0.35392 | 0.26956 | | |
| Portezuelo | 0.35525 | 0.28202 | | |
| Ránquil | 0.35683 | 0.37769 | X | |
| San Nicolás | 0.37907 | 0.40712 | X | |
| San Ignacio | 0.39983 | 0.41411 | X | |
| El Carmen | 0.39049 | 0.30707 | | |
| Antuco | 0.34138 | 0.30016 | | |
| Quilaco | 0.34255 | 0.39272 | X | |
| Contulmo | 0.35794 | 0.40358 | X | |
| Tirúa | 0.37874 | 0.42184 | | |
| Galvarino | 0.38968 | 0.40596 | X | |
| Melipeuco | 0.35643 | 0.29612 | | |
| Saavedra | 0.39414 | 0.42441 | | |
| Toltén | 0.38489 | 0.41456 | X | |
| Curarrehue | 0.36414 | 0.26478 | | |
| Lago Ranco | 0.38056 | 0.38847 | X | |
| San Juan de la Costa | 0.37502 | 0.26258 | | |
| San Pablo | 0.38082 | 0.43340 | | |
| Puerto Octay | 0.38112 | 0.40456 | X | |
| Los Muermos | 0.40197 | 0.41874 | X | |

Appendix 13 (cont.)

| | | | |
|---|---|---|---|
| Cochamó | 0.34592 | 0.33858 | X |
| Dalcahue | 0.38292 | 0.31701 | |
| Quemchi | 0.37436 | 0.40867 | X |
| Quinchao | 0.37570 | 0.40843 | X |
| Curaco De Vélez | 0.33566 | 0.22688 | |
| Puqueldón | 0.34395 | 0.33756 | X |
| Queilén | 0.35267 | 0.28707 | |
| Hualaihué | 0.37233 | 0.39347 | X |
| Palena | 0.30677 | 0.31991 | |
| Guaitecas | 0.30291 | 0.24461 | |
| Cisnes | 0.35724 | 0.33192 | X |
| Lago Verde | 0.28760 | 0.22455 | |
| Río Ibáñez | 0.32255 | 0.27164 | |
| Tortel | 0.25708 | 0.22455 | |
| O'Higgins | 0.25333 | 0.11809 | |
| Torres del Paine | 0.27263 | 0.22760 | |
| Río Verde | 0.24272 | 0.22760 | |
| Laguna Blanca | 0.26815 | 0.12113 | |
| San Gregorio | 0.29117 | 0.12113 | |
| Primavera | 0.28577 | 0.12113 | |
| Timaukel | 0.24960 | 0.12113 | |
| Antártica | 0.20091 | 0.27468 | |
| María Pinto | 0.38155 | 0.37334 | X |
| San Pedro | 0.36855 | 0.33017 | X |
| Alhué | 0.34660 | 0.40004 | X |
| Pirque | 0.40099 | 0.47718 | |

Table A13.3: Calculations to determine Communes Represented in Group 2

| **Group 2** | | | ***Puerto Aysén (±3.3%)*** | | ***Purén (±7.3%)*** | | ***Peumo (±3.8%)*** | | ***Puerto Natales (±4.0%)*** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **α** | **β** | ***[0.36420-0.38906] α = 0.37663*** | ***[0.37212-0.39752] β = 0.38482*** | ***[0.32998-0.38184] α = 0.35586*** | ***[0.35122-0.40654] β = 0.37888*** | ***[0.34526-0.37253] α = 0.35889*** | ***[0.35065-0.37836] β = 0.36451*** | ***[0.35592-0.38558] α = 0.37075*** | ***[0.32985-0.35734] β = 0.34359*** |
| Pozo Almonte | 0.34938 | 0.36762 | | | X | | X | | | |
| Pica | 0.32827 | 0.41394 | | | | | | | | |
| Mejillones | 0.33990 | 0.41114 | | | | | | | | |
| Tierra Amarilla | 0.35592 | 0.44205 | | | | | | | | |
| Huasco | 0.33773 | 0.44615 | | | | | | | | |
| Freirina | 0.32501 | 0.35710 | | | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Vicuña | 0.37932 | 0.37588 | X | X | | |
| Andacollo | 0.34745 | 0.42720 | | | | |
| Punitaqui | 0.34460 | 0.34536 | | | | |
| Monte Patria | 0.38804 | 0.38531 | X | | | |
| Combarbalá | 0.35762 | 0.36907 | | X | X | |
| Illapel | 0.38814 | 0.48699 | | | | |
| Los Vilos | 0.36732 | 0.41651 | | | | |
| Salamanca | 0.38007 | 0.39571 | X | X | | |
| La Ligua | 0.39011 | 0.46450 | | | | |
| Cabildo | 0.37035 | 0.38995 | X | X | | |
| Putaendo | 0.36074 | 0.35533 | | X | X | X |
| San Esteban | 0.36009 | 0.36759 | | X | X | |
| Papudo | 0.31724 | 0.31996 | | | | |
| Puchuncaví | 0.35611 | 0.45646 | | | | |
| Nogales | 0.37540 | 0.44876 | | | | |
| Catemu | 0.35359 | 0.35417 | | X | X | |
| Santa María | 0.35570 | 0.37834 | | X | X | |
| La Cruz | 0.35581 | 0.32345 | | | | |
| Hijuelas | 0.36409 | 0.37786 | | X | X | |
| Panquehue | 0.33056 | 0.25511 | | | | |
| Rinconada | 0.33127 | 0.39885 | | X | | |
| Llaillay | 0.37542 | 0.42445 | | | | |
| Olmué | 0.35931 | 0.39503 | | X | | |
| Casablanca | 0.37582 | 0.29771 | | | | |
| Algarrobo | 0.34071 | 0.22294 | | | | |
| El Tabo | 0.33312 | 0.33210 | | | | |
| Las Cabras | 0.37290 | 0.36947 | | X | | |
| Doñihue | 0.36615 | 0.44175 | | | | |
| Graneros | 0.38226 | 0.43196 | | | | |
| Mostazal | 0.37580 | 0.44000 | | | | |
| Pichilemu | 0.35444 | 0.39643 | | X | | |
| Peumo | 0.35889 | 0.36451 | | X | X | |
| San Vicente | 0.39875 | 0.29278 | | | | |
| Coínco | 0.32951 | 0.36457 | | | | |
| Quinta de Tilcoco | 0.35124 | 0.35636 | | X | X | |
| Olivar | 0.35427 | 0.37519 | | X | X | |
| Rengo | 0.40753 | 0.48589 | | | | |
| Malloa | 0.35587 | 0.33807 | | | | |
| Codegua | 0.34926 | 0.35165 | | X | X | |
| Peralillo | 0.34535 | 0.36616 | | X | X | |
| Santa Cruz | 0.39057 | 0.44618 | | | | |
| Chépica | 0.35865 | 0.36397 | | X | X | |
| Nancagua | 0.36318 | 0.27596 | | | | |
| Chimbarongo | 0.39049 | 0.37403 | | | | |
| Licantén | 0.33244 | 0.35597 | | X | | |
| Hualañé | 0.34539 | 0.37785 | | X | X | |
| Rauco | 0.34056 | 0.34314 | | | | |
| Sagrada Familia | 0.36747 | 0.33299 | | | | X |

Appendix 13 (cont.)

| | | | | | | |
|---|---|---|---|---|---|---|
| Teno | 0.38172 | 0.34132 | | | | X |
| Molina | 0.39710 | 0.46175 | | | | |
| Constitución | 0.40384 | 0.51309 | | | | |
| Empedrado | 0.31398 | 0.35063 | | | | |
| San Rafael | 0.33642 | 0.25635 | | | | |
| San Clemente | 0.39585 | 0.36052 | | | | |
| Chanco | 0.34428 | 0.34028 | | | | |
| Cauquenes | 0.39964 | 0.46094 | | | | |
| San Javier | 0.39638 | 0.41080 | | | | |
| Parral | 0.39641 | 0.45369 | | | | |
| Villa Alegre | 0.36093 | 0.25630 | | | | |
| Longaví | 0.38532 | 0.33302 | | | | X |
| Colbún | 0.36768 | 0.33343 | | | | X |
| Quirihue | 0.35140 | 0.44147 | | | | |
| San Carlos | 0.40697 | 0.42719 | | | | |
| Coelemu | 0.36425 | 0.38694 | X | X | | |
| Chillán Viejo | 0.37617 | 0.42733 | | | | |
| Bulnes | 0.37355 | 0.42879 | | | | |
| Quillón | 0.36199 | 0.36992 | | X | X | |
| Pemuco | 0.34166 | 0.26670 | | | | |
| Coihueco | 0.37864 | 0.35742 | | X | | |
| Pinto | 0.34591 | 0.37485 | | X | X | |
| Yungay | 0.36592 | 0.41946 | | | | |
| Florida | 0.34704 | 0.34620 | | | | |
| Hualqui | 0.37006 | 0.41412 | | | | |
| Santa Juana | 0.35541 | 0.39682 | | X | | |
| Yumbel | 0.37337 | 0.40305 | | X | | |
| Cabrero | 0.38126 | 0.44782 | | | | |
| San Rosendo | 0.31114 | 0.39213 | | | | |
| Laja | 0.37672 | 0.41927 | | | | |
| Nacimiento | 0.38227 | 0.47648 | | | | |
| Quilleco | 0.34796 | 0.36670 | | X | X | |
| Tucapel | 0.35560 | 0.43064 | | | | |
| Santa Bárbara | 0.37239 | 0.38369 | X | X | | |
| Mulchén | 0.38642 | 0.46617 | | | | |
| Negrete | 0.34062 | 0.39752 | | X | | |
| Arauco | 0.39336 | 0.42175 | | | | |
| Lebu | 0.38089 | 0.35309 | | X | | X |
| Los Alamos | 0.36978 | 0.44886 | | | | |
| Cañete | 0.38925 | 0.43201 | | | | |
| Renaico | 0.34295 | 0.39450 | | X | | |
| Collipulli | 0.37663 | 0.43908 | | | | |
| Lonquimay | 0.34726 | 0.33904 | | | | |
| Purén | 0.35586 | 0.37888 | | X | | |
| Los Sauces | 0.33596 | 0.35324 | | X | | |
| Ercilla | 0.34259 | 0.33975 | | | | |
| Lumaco | 0.35132 | 0.34488 | | | | |
| Traiguén | 0.37156 | 0.50319 | | | | |

Appendix 13 (cont.)

| | | | | | | |
|---|---|---|---|---|---|---|
| Victoria | 0.39185 | 0.49454 | | | | |
| Curacautín | 0.36627 | 0.44148 | | | | |
| Carahue | 0.38187 | 0.39711 | X | | | |
| Nueva Imperial | 0.39857 | 0.44492 | | | | |
| Perquenco | 0.32989 | 0.36871 | | X | | |
| Lautaro | 0.39038 | 0.45774 | | | | |
| Vilcún | 0.37686 | 0.38732 | X | X | | |
| Padre Las Casas | 0.41300 | 0.47973 | | | | |
| Teodoro Schmidt | 0.36287 | 0.35681 | | X | X | X |
| Freire | 0.38160 | 0.39463 | X | X | | |
| Cunco | 0.36993 | 0.40766 | | X | | |
| Pitrufquén | 0.37601 | 0.46734 | | | | |
| Gorbea | 0.36218 | 0.44727 | | | | |
| Loncoche | 0.37776 | 0.44857 | | | | |
| Villarrica | 0.40339 | 0.47864 | | | | |
| Pucón | 0.37447 | 0.43586 | | | | |
| Mariquina | 0.36895 | 0.37211 | | X | X | |
| Lanco | 0.36190 | 0.39568 | | X | | |
| Panguipulli | 0.39159 | 0.29877 | | | | |
| Máfil | 0.33409 | 0.36016 | | X | | |
| Los Lagos | 0.37276 | 0.39341 | X | X | | |
| Futrono | 0.36158 | 0.29354 | | | | |
| Corral | 0.32364 | 0.37573 | | | | |
| Paillaco | 0.37098 | 0.37716 | X | X | X | |
| La Unión | 0.39799 | 0.44828 | | | | |
| Río Bueno | 0.39085 | 0.40257 | | | | |
| Puyehue | 0.35120 | 0.34321 | | | | |
| Río Negro | 0.36095 | 0.38397 | | X | | |
| Purranque | 0.37375 | 0.41750 | | | | |
| Fresia | 0.35567 | 0.36390 | | X | X | |
| Frutillar | 0.36292 | 0.29791 | | | | |
| Puerto Varas | 0.39118 | 0.41906 | | | | |
| Llanquihue | 0.36484 | 0.43183 | | | | |
| Maullín | 0.36305 | 0.38447 | | X | | |
| Calbuco | 0.38901 | 0.39183 | X | | | |
| Ancud | 0.39846 | 0.45659 | | | | |
| Castro | 0.39791 | 0.49248 | | | | |
| Chonchi | 0.35499 | 0.34770 | | | | |
| Quellón | 0.37573 | 0.39457 | X | X | | |
| Chaitén | 0.33393 | 0.36557 | | X | | |
| Futaleufú | 0.28243 | 0.27013 | | | | |
| Puerto Aisén | 0.37663 | 0.38482 | X | X | | |
| Chile Chico | 0.31588 | 0.31481 | | | | |
| Cochrane | 0.29940 | 0.30509 | | | | |
| Puerto Natales | 0.37075 | 0.34359 | | | | X |
| Porvenir | 0.32366 | 0.33850 | | | | |
| Navarino | 0.29048 | 0.32040 | | | | |
| Tiltil | 0.36101 | 0.35662 | | X | X | X |

Appendix 13 (cont.)

| | | | | | |
|---|---|---|---|---|---|
| Lampa | 0.39873 | 0.42776 | | | |
| Curacaví | 0.37977 | 0.42228 | | | |
| Paine | 0.40693 | 0.45792 | | | |
| Calera de Tango | 0.36897 | 0.37339 | X | X | X |
| Isla de Maipo | 0.38202 | 0.42600 | | | |
| San José de Maipo | 0.35732 | 0.41163 | | | |

Table A13.4: Calculations to determine Communes Represented in Group 3

| **Group 3** | **α** | **β** | ***San Ramón (±15%)*** ***α = 0.36109*** ***0.30693-0.41526*** ***β = 0.40691*** ***0.34587-0.46795*** |
|---|---|---|---|
| Arica | 0.38217 | 0.47422 | |
| Iquique | 0.38707 | 0.42460 | X |
| Tocopilla | 0.31776 | 0.39770 | X |
| María Elena | 0.28125 | 0.33500 | |
| Calama | 0.37298 | 0.44612 | X |
| Antofagasta | 0.39703 | 0.43886 | X |
| Taltal | 0.29348 | 0.33730 | |
| Chañaral | 0.29975 | 0.36044 | |
| Diego de Almagro | 0.30973 | 0.38176 | X |
| Caldera | 0.30019 | 0.36544 | |
| Copiapó | 0.37079 | 0.43487 | X |
| Vallenar | 0.33964 | 0.39648 | X |
| La Serena | 0.37758 | 0.45002 | X |
| Coquimbo | 0.37814 | 0.42324 | X |
| Ovalle | 0.36213 | 0.38319 | X |
| Los Andes | 0.34675 | 0.28534 | |
| San Felipe | 0.34874 | 0.29615 | |
| Quintero | 0.31383 | 0.35550 | X |
| Calera | 0.34059 | 0.38898 | X |
| Quillota | 0.35406 | 0.28819 | |
| Concón | 0.32711 | 0.28873 | |
| Limache | 0.33325 | 0.36075 | X |
| Viña del Mar | 0.39595 | 0.36088 | X |
| Quilpué | 0.37066 | 0.30232 | |
| Villa Alemana | 0.36133 | 0.39748 | X |
| Valparaíso | 0.39473 | 0.51037 | |

Appendix 13 (cont.)

| | | | |
|---|---|---|---|
| El Quisco | 0.28847 | 0.33180 | |
| Cartagena | 0.30668 | 0.33018 | |
| San Antonio | 0.35843 | 0.40487 | X |
| Isla de Pascua | 0.25963 | 0.30373 | |
| Rancagua | 0.38676 | 0.46599 | X |
| Machalí | 0.32333 | 0.27159 | |
| San Fernando | 0.34855 | 0.38698 | X |
| Curicó | 0.36838 | 0.38528 | X |
| Talca | 0.38486 | 0.43280 | X |
| Linares | 0.35696 | 0.38744 | X |
| Chillán | 0.37793 | 0.45758 | X |
| Tomé | 0.34240 | 0.38169 | X |
| Penco | 0.33829 | 0.27923 | |
| Concepción | 0.38701 | 0.35370 | X |
| Talcahuano | 0.39165 | 0.45875 | X |
| San Pedro de la Paz | 0.35589 | 0.35599 | X |
| Chiguayante | 0.35622 | 0.37762 | X |
| Coronel | 0.36130 | 0.41803 | X |
| Lota | 0.34032 | 0.38405 | X |
| Los Angeles | 0.37881 | 0.41676 | X |
| Curanilahue | 0.32678 | 0.36823 | X |
| Angol | 0.34026 | 0.40716 | X |
| Temuco | 0.39102 | 0.46917 | |
| Valdivia | 0.37347 | 0.44318 | X |
| Osorno | 0.37455 | 0.44206 | X |
| Puerto Montt | 0.38054 | 0.42235 | X |
| Coihaique | 0.34093 | 0.29802 | |
| Punta Arenas | 0.36835 | 0.33687 | |
| Colina | 0.35484 | 0.36914 | X |
| Melipilla | 0.36097 | 0.37005 | X |
| Buin | 0.34839 | 0.36237 | X |
| San Bernardo | 0.39120 | 0.44537 | X |
| Padre Hurtado | 0.33289 | 0.36055 | X |
| Peñaflor | 0.34994 | 0.39014 | X |
| El Monte | 0.32085 | 0.35742 | X |
| Talagante | 0.34654 | 0.39362 | X |
| Puente Alto | 0.41300 | 0.47960 | |
| Lo Barnechea | 0.35357 | 0.40722 | X |
| Vitacura | 0.35629 | 0.34334 | |
| Las Condes | 0.39160 | 0.45856 | X |
| La Reina | 0.36170 | 0.42309 | X |
| Peñalolén | 0.38701 | 0.42439 | X |
| La Florida | 0.40359 | 0.45317 | X |
| Huechuraba | 0.35328 | 0.38509 | X |
| Recoleta | 0.37514 | 0.43859 | X |
| Providencia | 0.36871 | 0.39816 | X |
| Ñuñoa | 0.37823 | 0.48379 | |
| Macul | 0.36646 | 0.41598 | X |

Appendix 13 (cont.)

| | | | |
|---|---|---|---|
| Conchalí | 0.37179 | 0.40680 | X |
| Independencia | 0.34940 | 0.40985 | X |
| Santiago | 0.38470 | 0.50037 | |
| San Joaquín | 0.36198 | 0.40868 | X |
| La Granja | 0.37161 | 0.41811 | X |
| San Ramón | 0.36109 | 0.40691 | X |
| La Pintana | 0.38298 | 0.43755 | X |
| San Miguel | 0.35526 | 0.42238 | X |
| La Cisterna | 0.35766 | 0.41012 | X |
| El Bosque | 0.38048 | 0.44099 | X |
| Pedro Aguirre Cerda | 0.36702 | 0.29562 | |
| Lo Espejo | 0.36654 | 0.41865 | X |
| Quilicura | 0.37015 | 0.38665 | X |
| Renca | 0.37185 | 0.41069 | X |
| Quinta Normal | 0.36398 | 0.42675 | X |
| Cerro Navia | 0.37516 | 0.41644 | X |
| Lo Prado | 0.36407 | 0.39464 | X |
| Estación Central | 0.37110 | 0.44605 | X |
| Cerrillos | 0.35235 | 0.38248 | X |
| Pudahuel | 0.38389 | 0.42371 | X |
| Maipú | 0.41139 | 0.45370 | X |

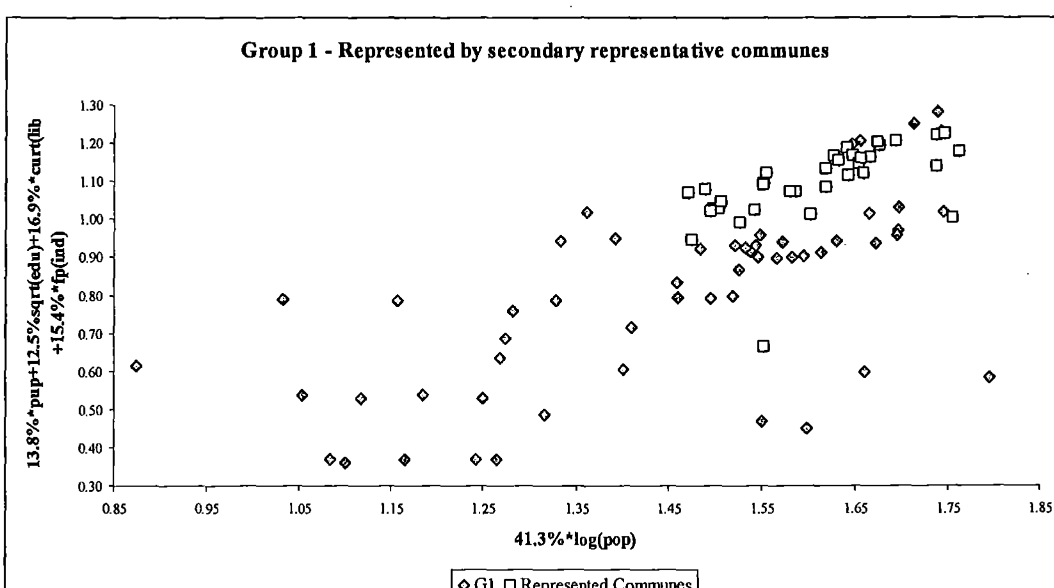



Figure A13.1: Group 1 – The total 91 communes and the 36 represented communes

Appendix 13 (cont.)

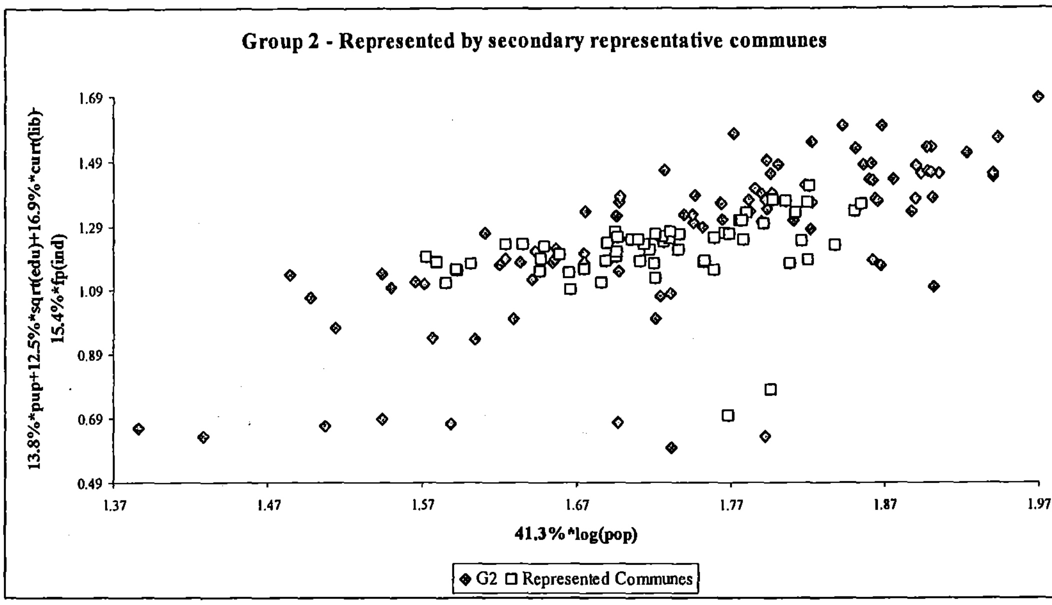



Figure A13.2: Group 2 – The total 156 communes and the 60 represented communes

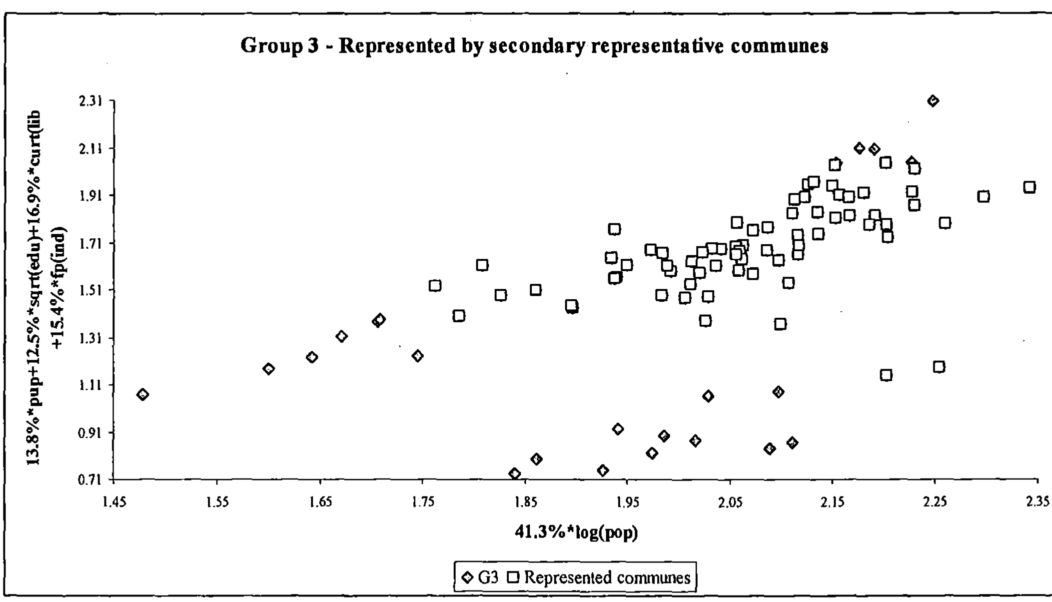


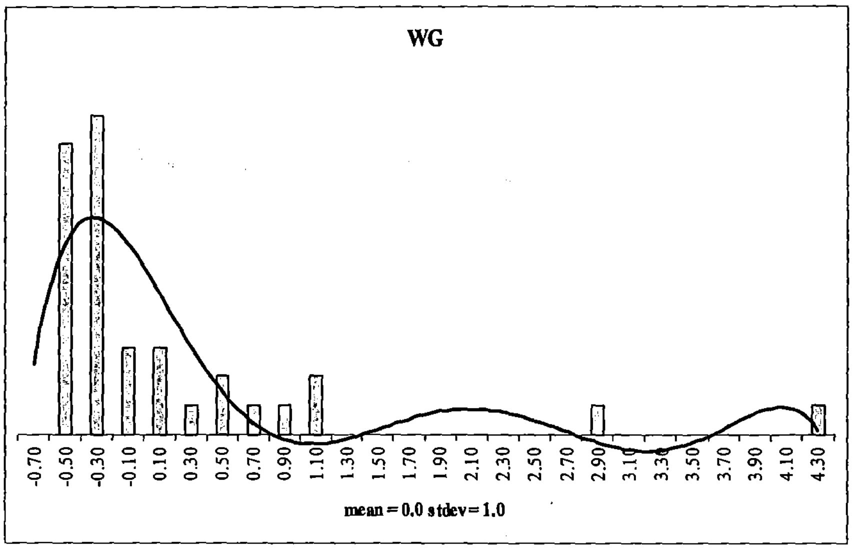

Figure A13.3: Group 3 – The total 95 communes and the 71 represented communes

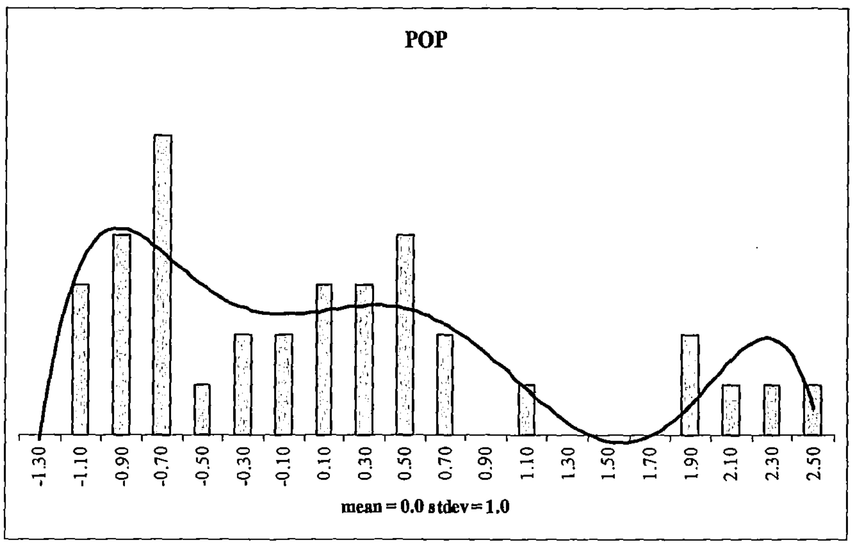
Appendix 13 (cont.)

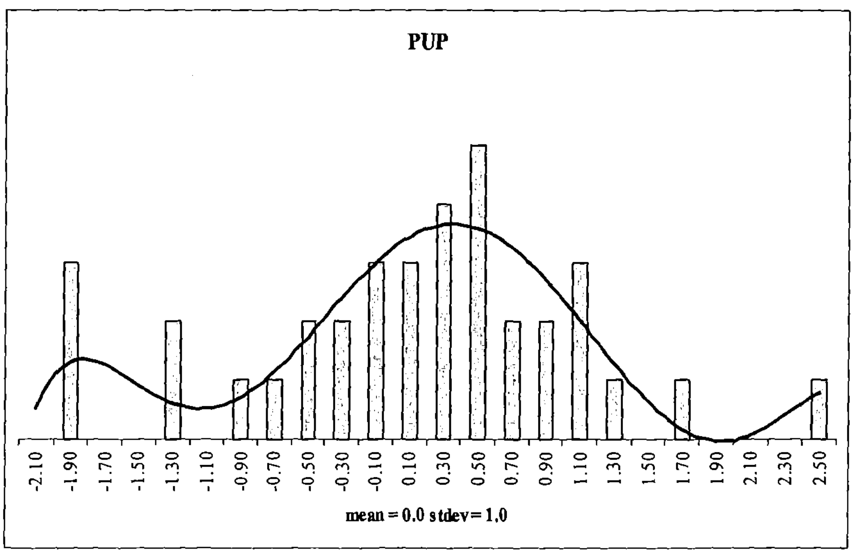
# APPENDIX 14

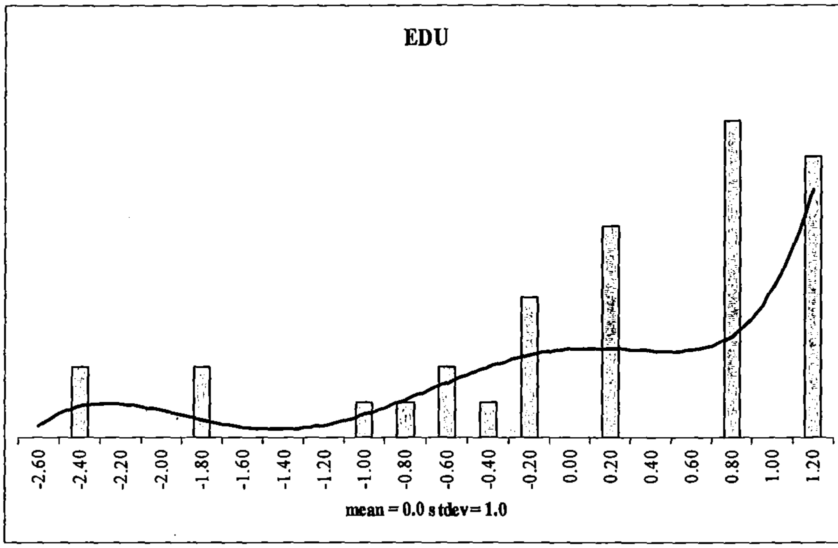
Mean and Standard Deviation for the Explanatory and Explained Variables of the Represented Communes

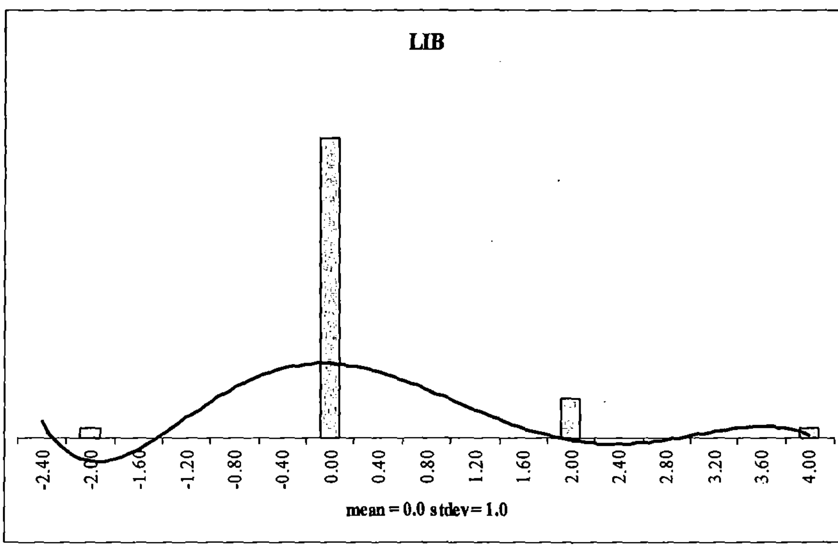
Figure A14.1: Mean and Standard Deviation for the Explanatory and Explained Variables of the Represented Communes of Group 1

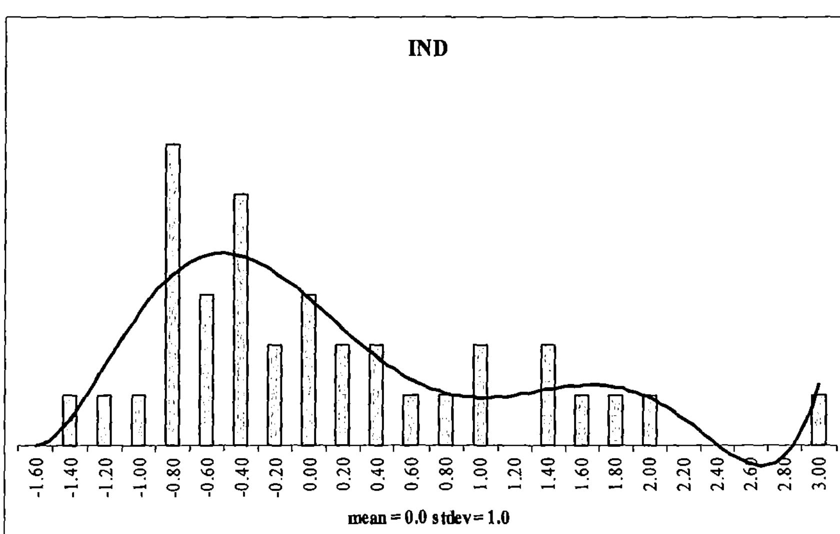


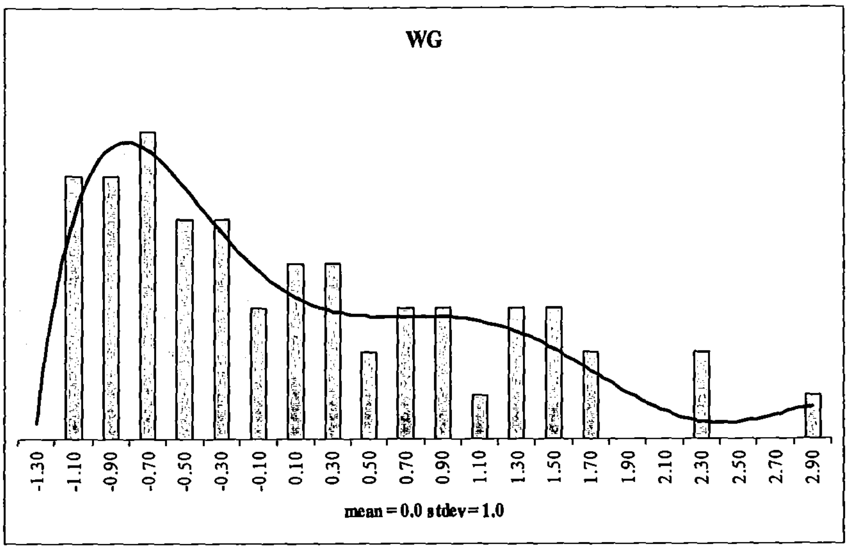


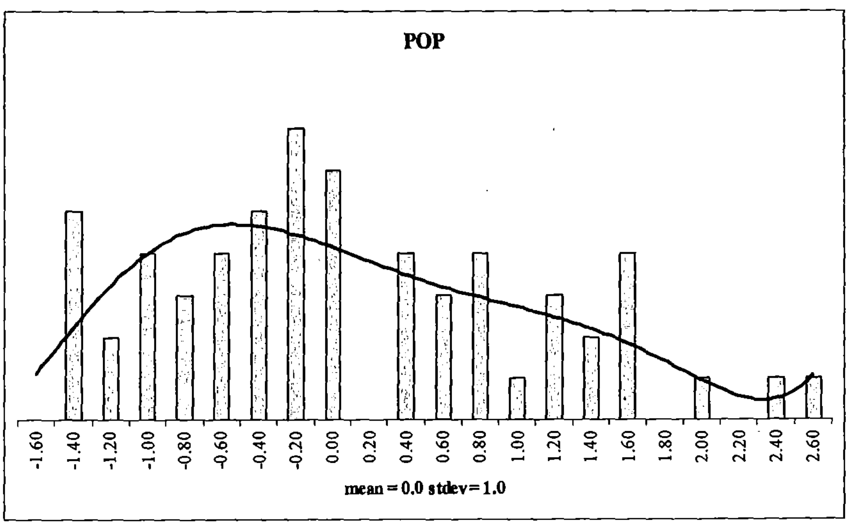



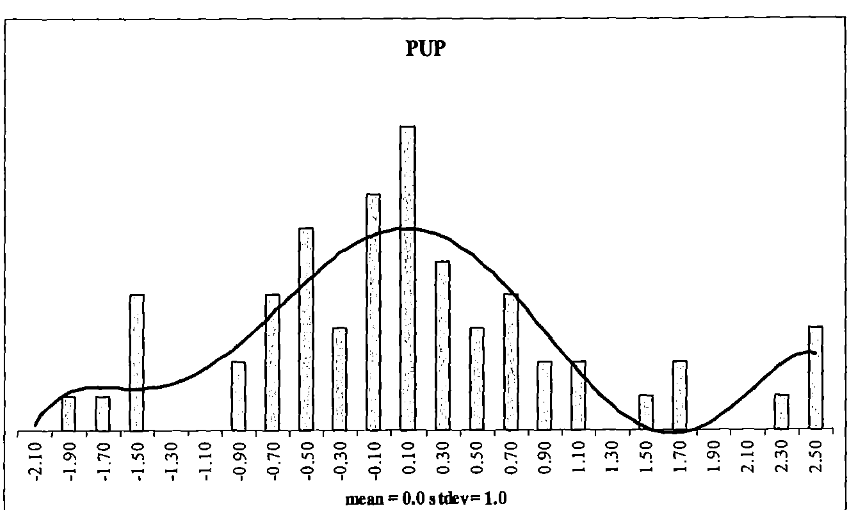




Appendix 14 (cont.)

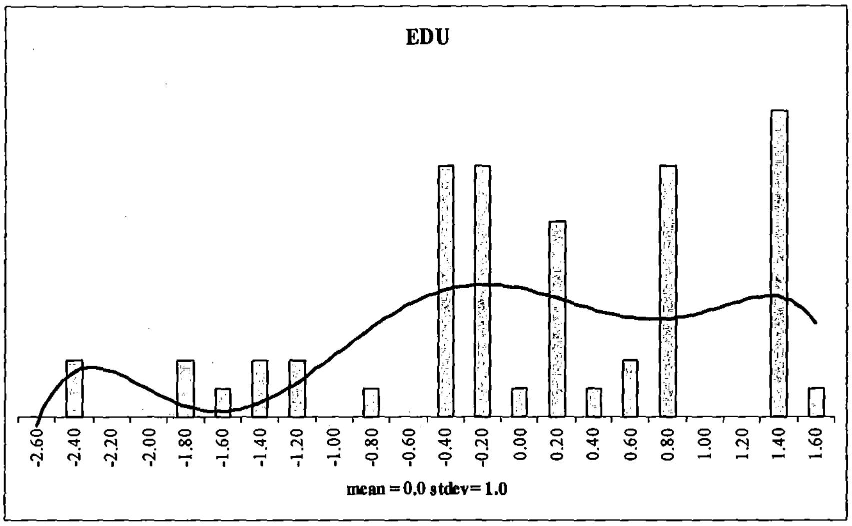
Figure A14.2: Mean and Standard Deviation for the Explanatory and Explained Variables of the Represented Communes of Group 2

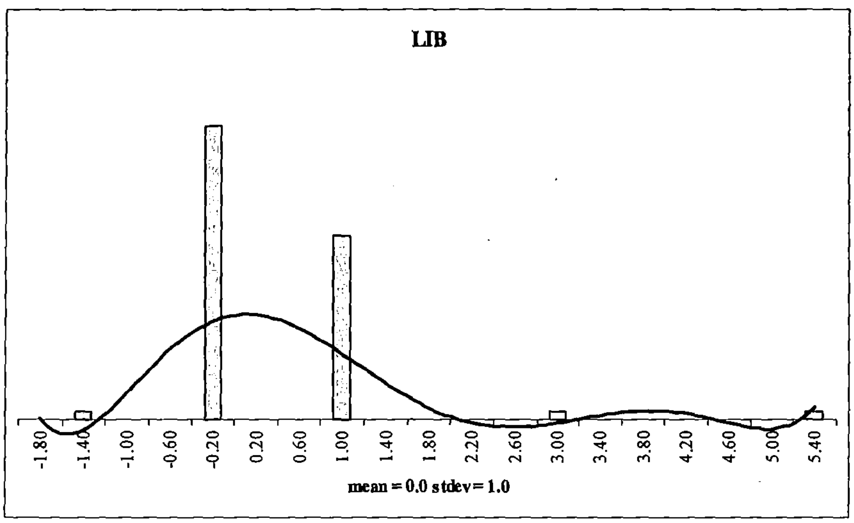


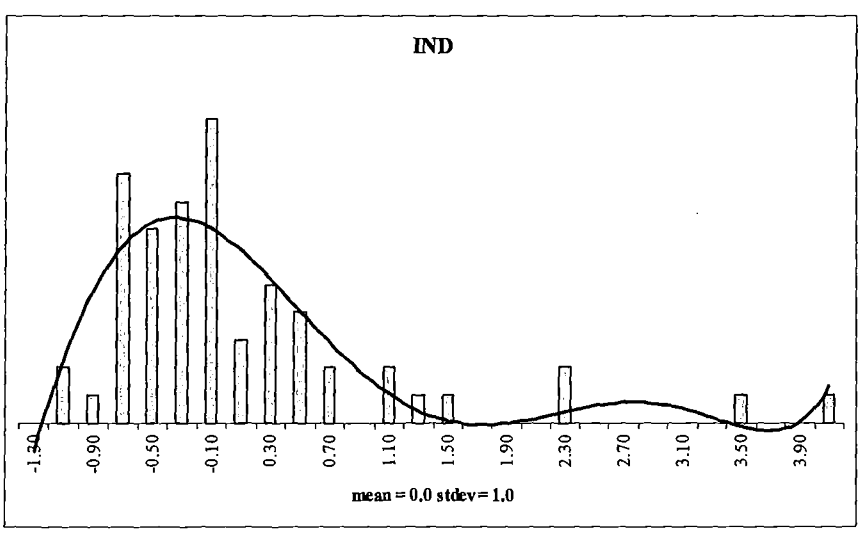




Appendix 14 (cont.)

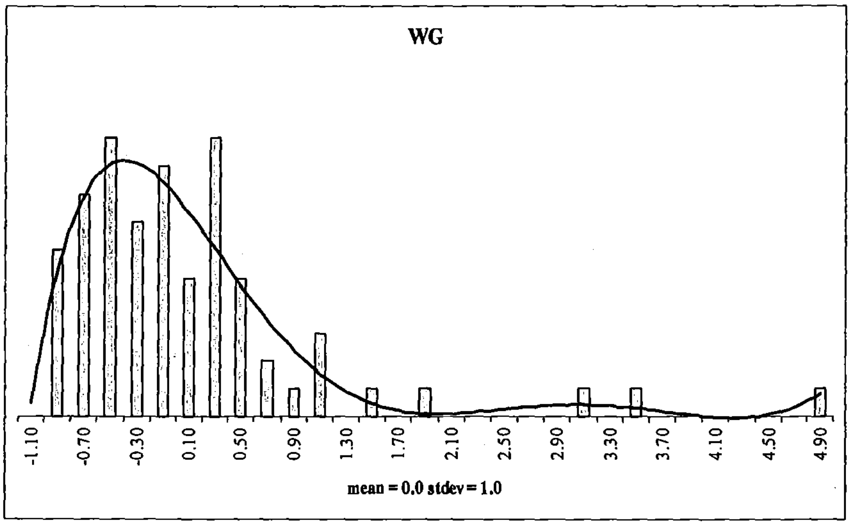


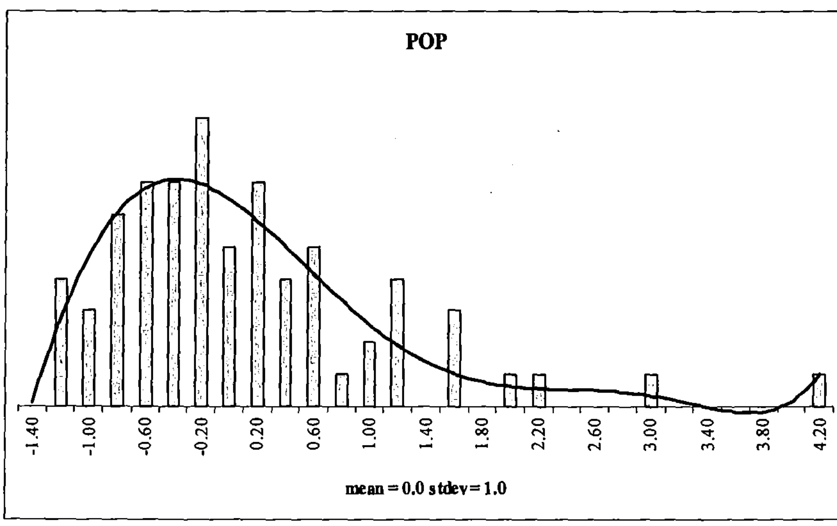



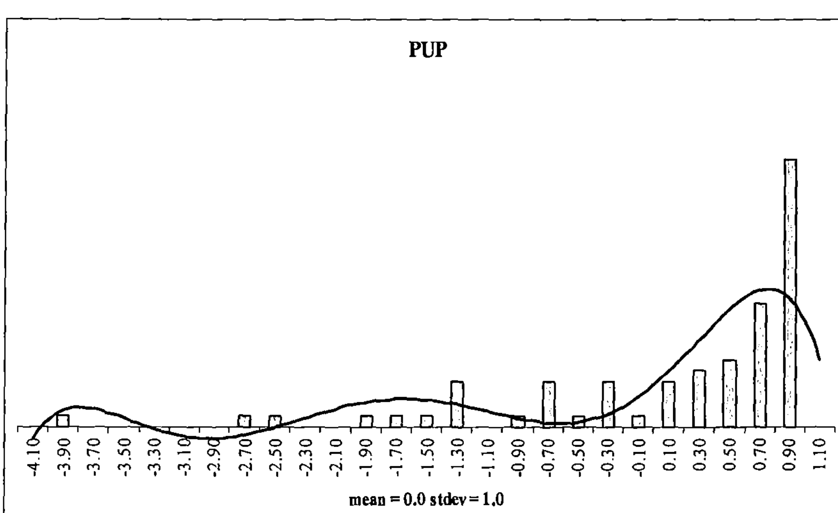




Appendix 14 (cont.)

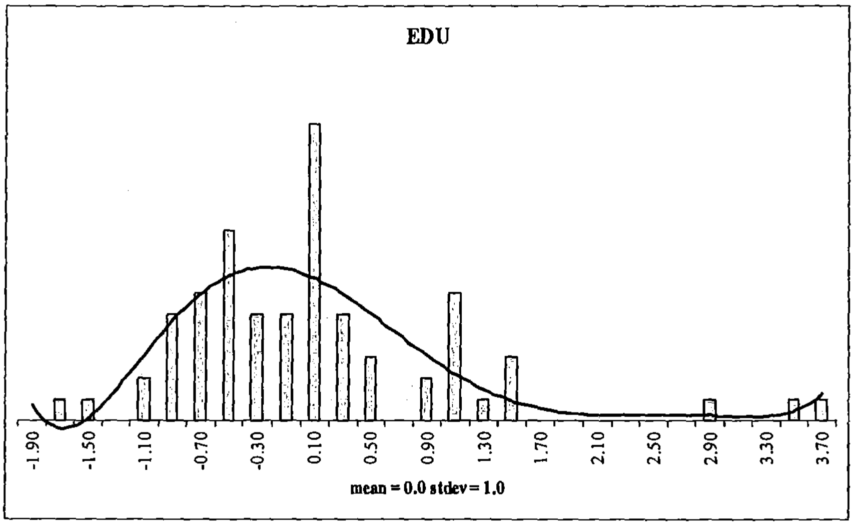
Figure A14.3: Mean and Standard Deviation for the Explanatory and Explained Variables of the Represented Communes of Group 3

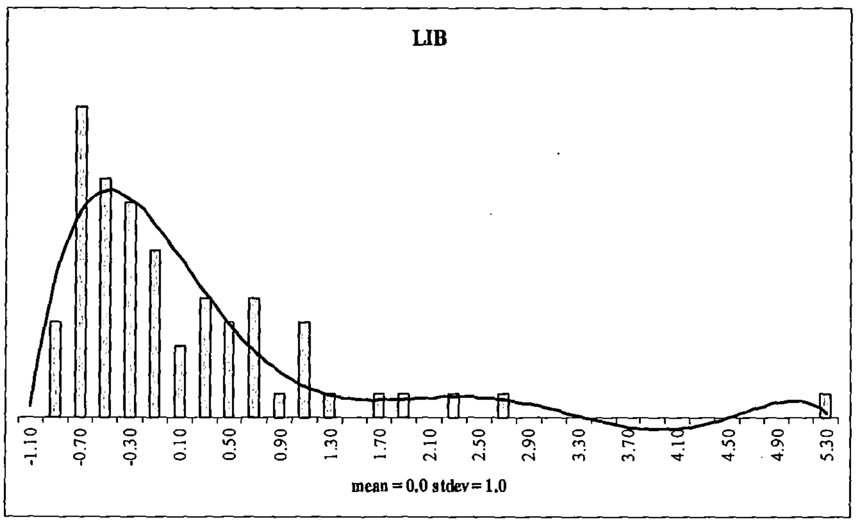


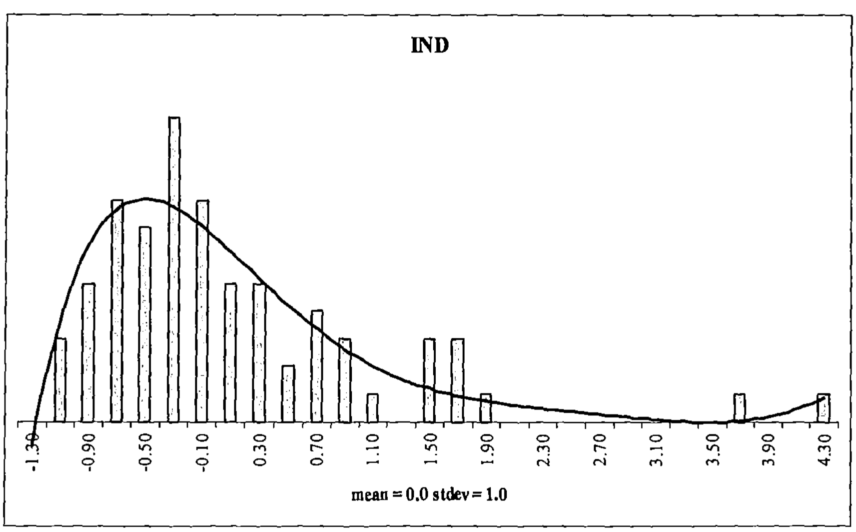




Appendix 14 (cont.)




Appendix 14 (cont.)

# APPENDIX 15

Table A15.1: Data Collected for the Three Groups (Initial Models)

| Group 1 | | | |
|---|---|---|---|
| Year | POP (people) | LIB (number) | WG (tonnes/month) |
| 1998 | 9,650 | 1 | 71.40 |
| 1999 | 9,811 | 1 | 77.48 |
| 2000 | 9,975 | 1 | 83.55 |
| 2001 | 10,142 | 1 | 89.62 |
| 2002 | 10,343 | 1 | 106.02 |
| 2003 | 10,516 | 1 | 104.73 |

| Group 2 | | | |
|---|---|---|---|
| Year | POP (people) | LIB (number) | WG (tonnes/month) |
| 1997 | 13,447 | 1 | 151.33 |
| 1998 | 13,355 | 1 | 166.54 |
| 1999 | 13,263 | 1 | 181.54 |
| 2000 | 13,172 | 1 | 224.23 |
| 2001 | 13,082 | 1 | 266.34 |
| 2002 | 12,868 | 1 | 207.58 |

| Group 3 | | | |
|---|---|---|---|
| Year | POP (people) | PUP (number) | WG (tonnes/month) |
| 1992 | 100,817 | 1 | 2,099.75 |
| 1993 | 100,210 | 1 | 2,230.08 |
| 1994 | 99,606 | 1 | 2,448.00 |
| 1995 | 99,006 | 1 | 2,518.08 |
| 1996 | 98,410 | 1 | 2,549.42 |
| 1997 | 97,817 | 1 | 2,598.25 |
| 1998 | 97,228 | 1 | 3,108.58 |
| 1999 | 96,642 | 1 | 3,125.42 |
| 2000 | 96,060 | 1 | 3,120.08 |
| 2001 | 95,481 | 1 | 2,901.42 |
| 2002 | 94,906 | 1 | 2,830.25 |

# APPENDIX 16

Artificial Neural Networks Results (Initial Models)

Group 1: Jordan Network

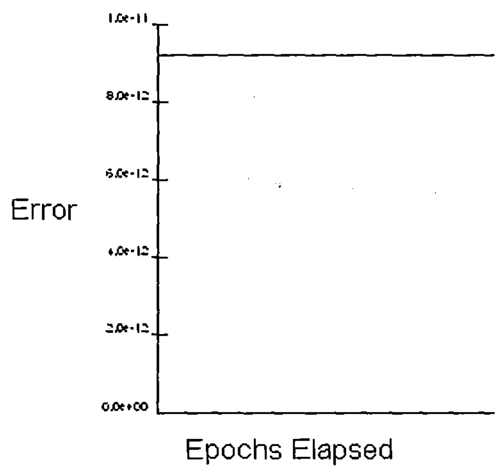



Figure A16.1: Training Set Average Error versus Epochs Elapsed

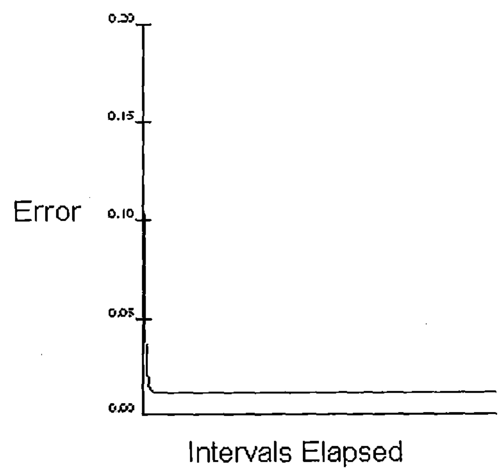



Figure A16.2: Testing Ser Average Error versus Intervals Elapsed

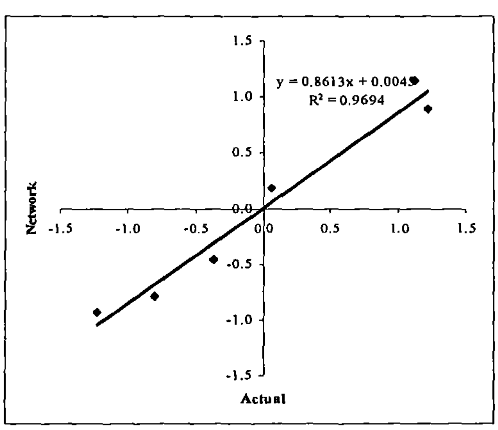



Figure A16.3: Actual Outputs versus Network Outputs (Whole Dataset)

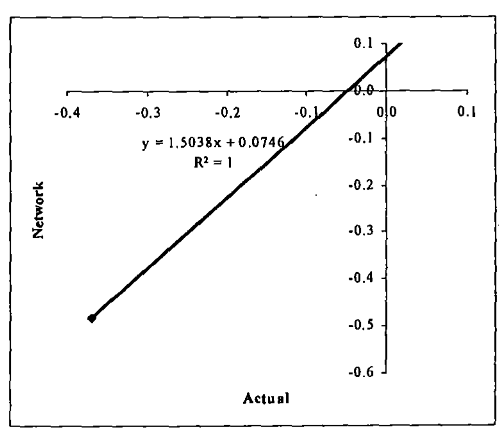



Figure A16.4: Actual Outputs versus Network Outputs (Validation Set)

Group 2: Elman Network

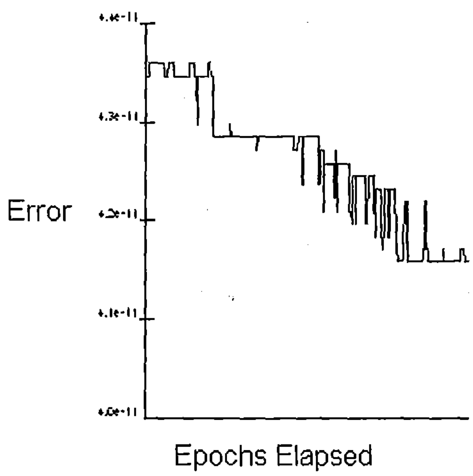



Figure A16.5: Training Set Average Error versus Epochs Elapsed

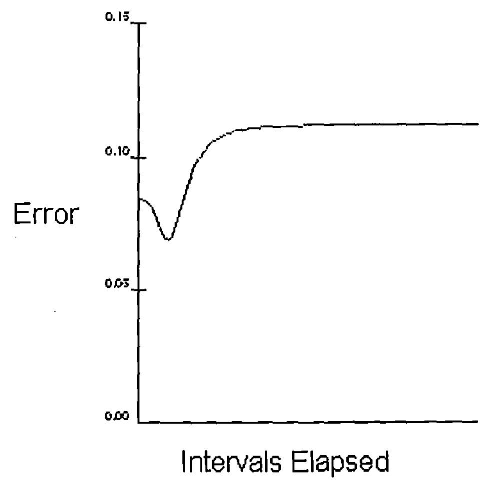



Figure A16.6: Testing Ser Average Error versus Intervals Elapsed

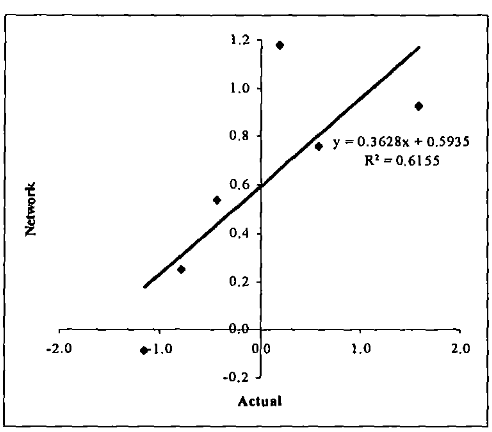



Figure A16.7: Actual Outputs versus Network Outputs (Whole Dataset)

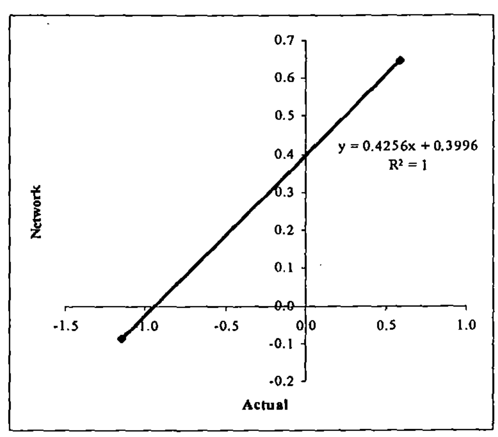



Figure A16.8: Actual Outputs versus Network Outputs (Validation Set)

Appendix 16 (cont.)

Group 3: Jordan Network

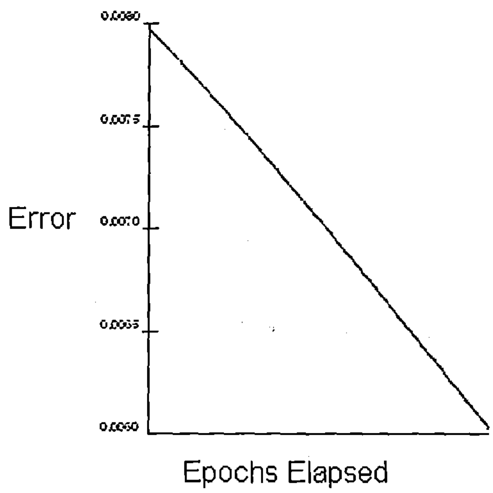



Figure A16.9: Training Set Average Error versus Epochs Elapsed

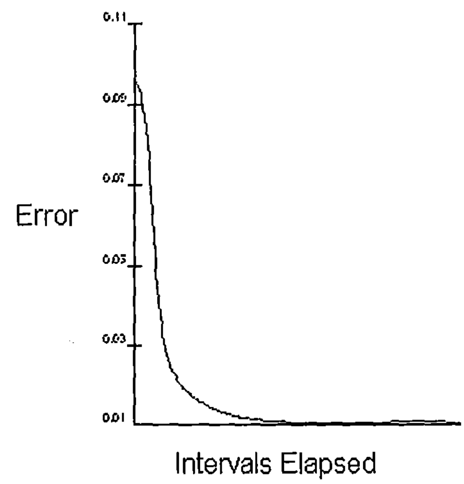



Figure A16.10: Testing Ser Average Error versus Intervals Elapsed

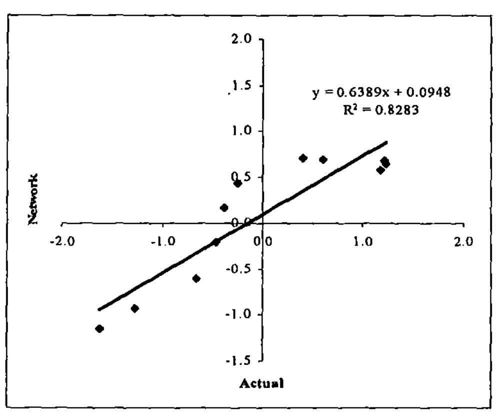



Figure A16.11: Actual Outputs versus Network Outputs (Whole Dataset)

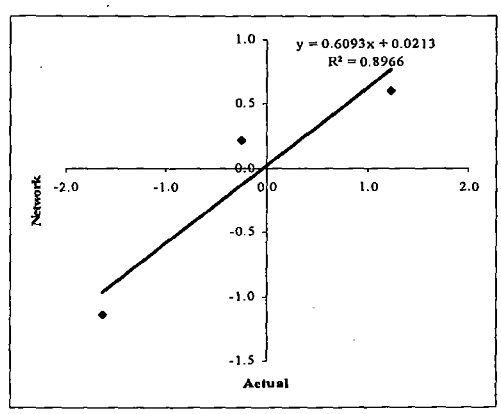



Figure A16.12: Actual Outputs versus Network Outputs (Validation Set)

NeuroShell 2 – Release 4.0 (1993-1998) by Ward Systems Group®, Inc.
Licensed to Lincoln University.

Appendix 16 (cont.)

# APPENDIX 17

Artificial Neural Networks Forecasts, Errors and Yearly Variations in Waste for Groups 1, 2 and 3 (Initial Models)

Table A17.1: Artificial Neural Networks Performance (Initial Models)

Group 1 $R^2 = 0.75$

| Year | WG (tonnes/month) | Jordan Forecast Model (tonnes/month) | Error (%) | Yearly Variation in Waste (%) |
|---|---|---|---|---|
| 1998 | 71.40 | 75.55 | 5.8% | |
| 1999 | 77.48 | 77.56 | 0.1% | 2.66% |
| 2000 | 83.55 | 82.29 | -1.5% | 6.11% |
| 2001 | 89.62 | 91.36 | 1.9% | 11.01% |
| 2002 | 106.02 | 101.42 | -4.3% | 11.01% |
| 2003 | 104.73 | 90.50 | -13.6% | -10.76% |
| 2004 | | 91.03 | | 0.59% |
| 2005 | | 92.04 | | 1.11% |
| 2006 | | 93.90 | | 2.02% |
| 2007 | | 96.79 | | 3.07% |
| 2008 | | 99.78 | | 3.08% |
| 2009 | | 101.69 | | 1.92% |
| 2010 | | 102.61 | | 0.90% |

2001-2010
Yearly Variation: 1.5%
Variation: 14.5%

Group 2 $R^2 = 0.25$

| Year | WG (tonnes/month) | Elman Forecast Model (tonnes/month) | Error (%) | Yearly Variation in Waste (%) |
|---|---|---|---|---|
| 1997 | 151.33 | 195.89 | 29.4% | |
| 1998 | 166.54 | 210.02 | 26.1% | 7.21% |
| 1999 | 181.54 | 222.19 | 22.4% | 5.80% |
| 2000 | 224.23 | 231.56 | 3.3% | 4.22% |
| 2001 | 266.34 | 238.67 | -10.4% | 3.07% |
| 2002 | 207.58 | 215.91 | 4.0% | -9.54% |
| 2003 | | 220.51 | | 2.13% |
| 2004 | | 224.36 | | 1.74% |
| 2005 | | 227.37 | | 1.34% |
| 2006 | | 229.77 | | 1.06% |
| 2007 | | 231.71 | | 0.84% |
| 2008 | | 233.28 | | 0.68% |
| 2009 | | 234.53 | | 0.54% |
| 2010 | | 235.53 | | 0.42% |

2002-2010
Yearly Variation: 1.6%
Variation: 13.5%

Group 3 $R^2 = 0.80$

| Year | WG (tonnes/month) | Jordan Forecast Model (tonnes/month) | Error (%) | Yearly Variation in Waste (%) |
|---|---|---|---|---|
| 1992 | 2,099.75 | 2272.92 | 8.2% | |
| 1993 | 2,230.08 | 2351.88 | 5.5% | 3.47% |
| 1994 | 2,448.00 | 2465.92 | 0.7% | 4.85% |
| 1995 | 2,518.08 | 2609.19 | 3.6% | 5.81% |
| 1996 | 2,549.42 | 2746.37 | 7.7% | 5.26% |
| 1997 | 2,598.25 | 2840.99 | 9.3% | 3.45% |
| 1998 | 3,108.58 | 2892.40 | -7.0% | 1.81% |
| 1999 | 3,125.42 | 2917.86 | -6.6% | 0.88% |
| 2000 | 3,120.08 | 2930.37 | -6.1% | 0.43% |
| 2001 | 2,901.42 | 2936.57 | 1.2% | 0.21% |
| 2002 | 2,830.25 | 2745.13 | -3.0% | -6.52% |
| 2003 | | 2779.43 | | 1.25% |
| 2004 | | 2832.42 | | 1.91% |
| 2005 | | 2894.40 | | 2.19% |
| 2006 | | 2940.47 | | 1.59% |
| 2007 | | 2963.43 | | 0.78% |
| 2008 | | 2973.04 | | 0.32% |
| 2009 | | 2976.97 | | 0.13% |
| 2010 | | 2978.53 | | 0.05% |

2002-2010
Yearly Variation: 0.6%
Variation: 5.2%

# APPENDIX 18

Table A18.1: Data Collected for the Three Groups (Improved Models)

| Group 1 | | | | |
|---|---|---|---|---|
| Year | POP (people) | LIB (number) | PCWG (kg/pc-day) | WG (tonnes/month) |
| 1998 | 9,650 | 1 | 0.24 | 71.40 |
| 1999 | 9,811 | 1 | 0.26 | 77.48 |
| 2000 | 9,975 | 1 | 0.27 | 83.55 |
| 2001 | 10,142 | 1 | 0.29 | 89.62 |
| 2002 | 10,343 | 1 | 0.34 | 106.02 |
| 2003 | 10,516 | 1 | 0.33 | 104.73 |

| Group 2 | | | | |
|---|---|---|---|---|
| Year | POP (people) | LIB (number) | PCWG (kg/pc-day) | WG (tonnes/month) |
| 1997 | 13,447 | 1 | 0.37 | 151.33 |
| 1998 | 13,355 | 1 | 0.41 | 166.54 |
| 1999 | 13,263 | 1 | 0.45 | 181.54 |
| 2000 | 13,172 | 1 | 0.56 | 224.23 |
| 2001 | 13,082 | 1 | 0.67 | 266.34 |
| 2002 | 12,868 | 1 | 0.53 | 207.58 |

| Group 3 | | | | |
|---|---|---|---|---|
| Year | POP (people) | PUP (number) | PCWG (kg/pc-day) | WG (tonnes/month) |
| 1992 | 100,817 | 1 | 0.68 | 2,099.75 |
| 1993 | 100,210 | 1 | 0.73 | 2,230.08 |
| 1994 | 99,606 | 1 | 0.81 | 2,448.00 |
| 1995 | 99,006 | 1 | 0.84 | 2,518.08 |
| 1996 | 98,410 | 1 | 0.85 | 2,549.42 |
| 1997 | 97,817 | 1 | 0.87 | 2,598.25 |
| 1998 | 97,228 | 1 | 1.05 | 3,108.58 |
| 1999 | 96,642 | 1 | 1.06 | 3,125.42 |
| 2000 | 96,060 | 1 | 1.07 | 3,120.08 |
| 2001 | 95,481 | 1 | 1.00 | 2,901.42 |
| 2002 | 94,906 | 1 | 0.98 | 2,830.25 |

# APPENDIX 19

Artificial Neural Networks Results (Improved Models)

Group 1: MLP Network

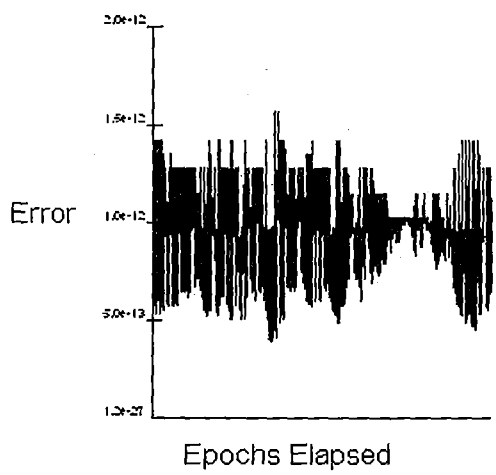



Figure A19.1 Training Set Average Error versus Epochs Elapsed

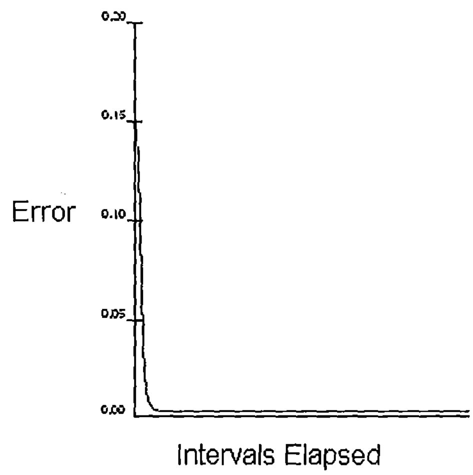



Figure A19.2 Testing Set Average Error versus Intervals Elapsed

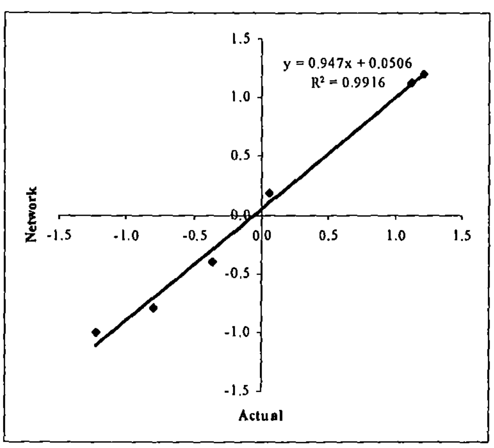



Figure A19.3: Actual Outputs versus Network Outputs (Whole Dataset)

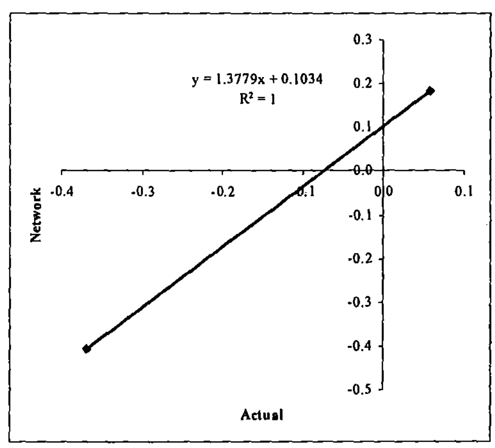



Figure A19.4: Actual Outputs versus Network Outputs (Validation Set)

Group 2: MLP Network

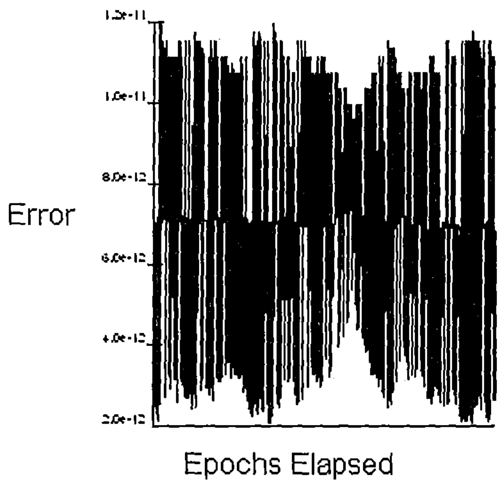



Figure A19.5 Training Set Average Error versus Epochs Elapsed

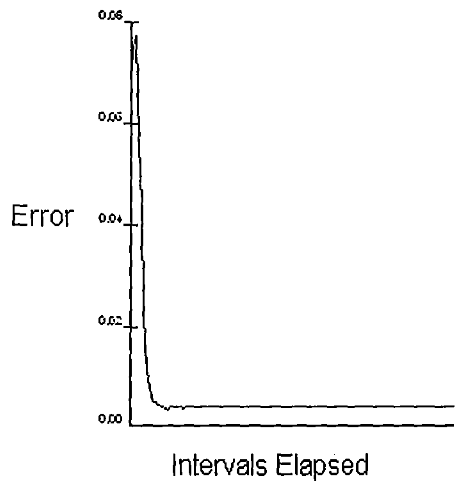



Figure A19.6 Testing Set Average Error versus Intervals Elapsed

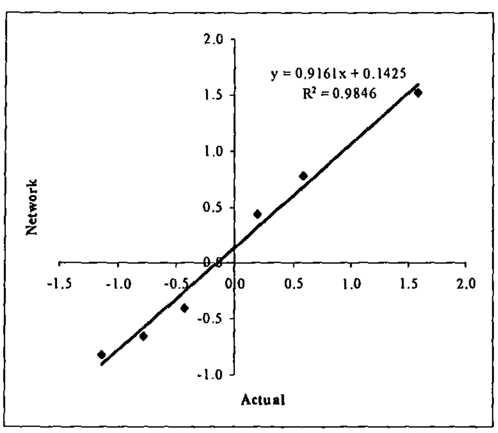



Figure A19.7: Actual Outputs versus Network Outputs (Whole Dataset)

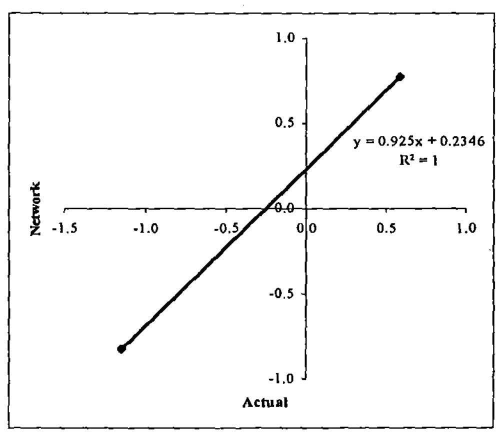



Figure A19.8: Actual Outputs versus Network Outputs (Validation Set)

Group 3: Jordan Network

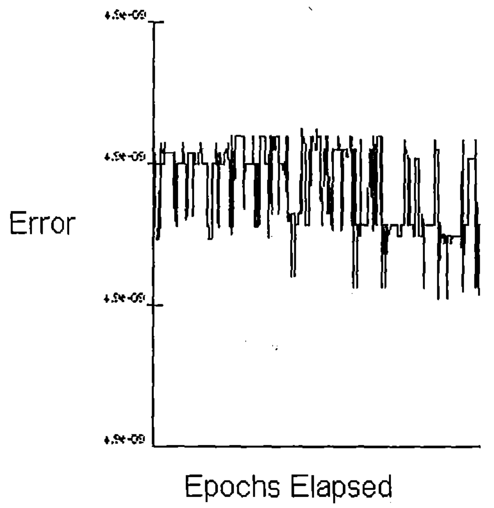



Figure A19.9 Training Set Average Error versus Epochs Elapsed

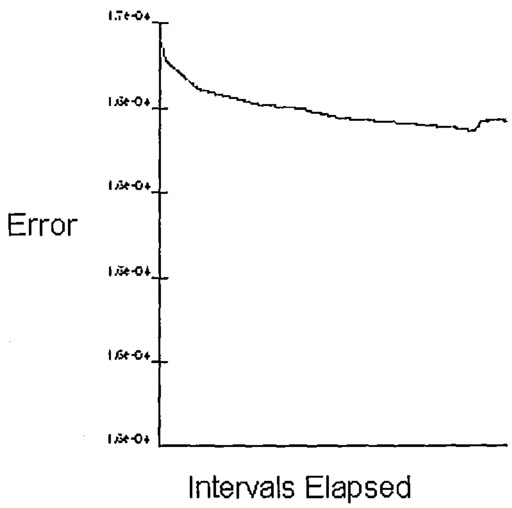



Figure A19.10 Testing Set Average Error versus Intervals Elapsed

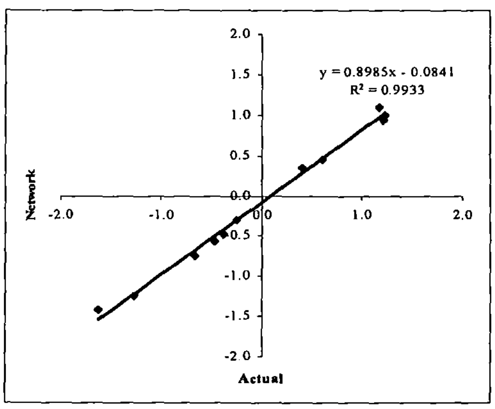



Figure A19.11: Actual Outputs versus Network Outputs (Whole Dataset)

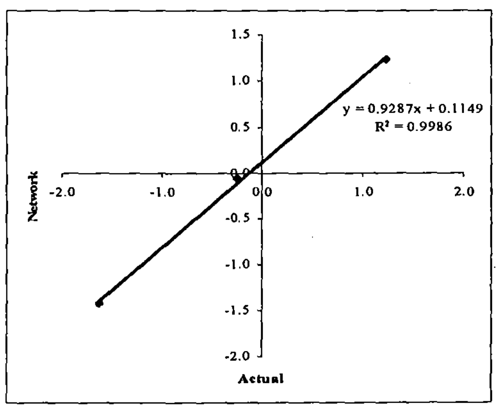



Figure A19.12: Actual Outputs versus Network Outputs (Validation Set)

NeuroShell 2 – Release 4.0 (1993-1998) by Ward Systems Group®, Inc.
Licensed to Lincoln University.

Appendix 19 (cont.)

# APPENDIX 20

Artificial Neural Networks Forecasts, Errors and Yearly Variations in Waste for Groups 1, 2 and 3 (Improved Models)

Table A20.1: Artificial Neural Networks Performance (Improved Models)

Group 1 $R^2 = 0.81$

| Year | WG (tonnes/month) | MLP Forecast Model (tonnes/month) | Error (%) | Yearly Variation in Waste (%) |
|---|---|---|---|---|
| 1998 | 71.40 | 74.59 | 4.5% | |
| 1999 | 77.48 | 77.48 | 0.0% | 3.87% |
| 2000 | 83.55 | 83.03 | -0.6% | 7.17% |
| 2001 | 89.62 | 91.40 | 2.0% | 10.08% |
| 2002 | 106.02 | 105.88 | -0.1% | 15.84% |
| 2003 | 104.73 | 102.95 | -1.7% | -2.77% |
| 2004 | | 90.11 | | -12.48% |
| 2005 | | 90.71 | | 0.67% |
| 2006 | | 92.20 | | 1.65% |
| 2007 | | 95.46 | | 3.53% |
| 2008 | | 99.24 | | 3.95% |
| 2009 | | 101.29 | | 2.07% |
| 2010 | | 102.12 | | 0.83% |

2001-2010
Yearly Variation: 1.5%
Variation: 13.9%

Group 2 $R^2 = 0.91$

| Year | WG (tonnes/month) | MLP Forecast Model (tonnes/month) | Error (%) | Yearly Variation in Waste (%) |
|---|---|---|---|---|
| 1997 | 151.33 | 164.83 | 8.9% | |
| 1998 | 166.54 | 171.85 | 3.2% | 4.26% |
| 1999 | 181.54 | 182.81 | 0.7% | 6.38% |
| 2000 | 224.23 | 232.27 | 3.6% | 27.06% |
| 2001 | 266.34 | 263.69 | -1.0% | 13.53% |
| 2002 | 207.58 | 204.54 | -1.5% | -22.43% |
| 2003 | | 208.28 | | 1.83% |
| 2004 | | 212.45 | | 2.00% |
| 2005 | | 218.83 | | 3.00% |
| 2006 | | 226.42 | | 3.47% |
| 2007 | | 232.87 | | 2.85% |
| 2008 | | 237.04 | | 1.79% |
| 2009 | | 239.41 | | 1.00% |
| 2010 | | 240.75 | | 0.56% |

2002-2010
Yearly Variation: 1.9%
Variation: 16.0%

Group 3 $R^2 = 0.98$

| Year | WG (tonnes/month) | Jordan Forecast Model (tonnes/month) | Error (%) | Yearly Variation in Waste (%) |
|---|---|---|---|---|
| 1992 | 2,099.75 | 2172.28 | 3.5% | |
| 1993 | 2,230.08 | 2237.94 | 0.4% | 3.02% |
| 1994 | 2,448.00 | 2414.67 | -1.4% | 7.90% |
| 1995 | 2,518.08 | 2481.36 | -1.5% | 2.76% |
| 1996 | 2,549.42 | 2514.25 | -1.4% | 1.33% |
| 1997 | 2,598.25 | 2573.39 | -1.0% | 2.35% |
| 1998 | 3,108.58 | 3081.74 | -0.9% | 19.75% |
| 1999 | 3,125.42 | 3041.07 | -2.7% | -1.32% |
| 2000 | 3,120.08 | 3022.12 | -3.1% | -0.62% |
| 2001 | 2,901.42 | 2847.28 | -1.9% | -5.79% |
| 2002 | 2,830.25 | 2930.78 | 3.6% | 2.93% |
| 2003 | | 2705.75 | | -7.68% |
| 2004 | | 2705.38 | | -0.01% |
| 2005 | | 2706.14 | | 0.03% |
| 2006 | | 2873.20 | | 6.17% |
| 2007 | | 3043.65 | | 5.93% |
| 2008 | | 3007.61 | | -1.18% |
| 2009 | | 2938.19 | | -2.31% |
| 2010 | | 2854.12 | | -2.86% |

2002-2010
Yearly Variation: 0.1%
Variation: 0.8%

# APPENDIX 21

Conversion Factors, Forecasted Figures and Plots of Waste Generation Levels for the Represented Communes of Groups 1, 2 and 3

# Table A21.1: Conversion Factors and Forecasted Levels of Waste Generation for the Represented Communes of Group 1

**Group 1**

| ***Conversion Factors*** | | | ***-2.89%*** | ***-12.48%*** | ***0.67%*** | ***1.65%*** | ***3.53%*** | ***3.95%*** | ***2.07%*** | ***0.83%*** |
|---|---|---|---|---|---|---|---|---|---|---|
| (tonnes/month) | WG01 (*) | WG02 (**) | *WG03* | *WG04* | *WG05* | *WG06* | *WG07* | *WG08* | *WG09* | *WG10* |
| Representative Communes | 89.62 | 106.02 | *102.95* | *90.11* | *90.71* | *92.20* | *95.46* | *99.24* | *101.29* | *102.12* |
| San Pedro de Atacama | 58.25 | 32.50 | *31.56* | *27.62* | *27.81* | *28.27* | *29.26* | *30.42* | *31.05* | *31.31* |
| La Higuera | 32.50 | 39.50 | *38.36* | *34.57* | *34.80* | *35.38* | *36.63* | *38.07* | *38.86* | *39.18* |
| Canela | 150.00 | 150.00 | *145.66* | *131.29* | *132.16* | *134.34* | *139.09* | *144.59* | *147.58* | *148.79* |
| Petorca | 124.00 | 136.00 | *132.07* | *119.03* | *119.83* | *121.80* | *126.11* | *131.09* | *133.80* | *134.91* |
| Navidad | 50.00 | 50.00 | *48.55* | *43.76* | *44.05* | *44.78* | *46.36* | *48.20* | *49.19* | *49.60* |
| La Estrella | 146.00 | 20.00 | *19.42* | *17.50* | *17.62* | *17.91* | *18.55* | *19.28* | *19.68* | *19.84* |
| Marchihue | 144.00 | 55.00 | *53.41* | *48.14* | *48.46* | *49.26* | *51.00* | *53.02* | *54.11* | *54.56* |
| Paredones | 83.00 | 48.00 | *46.61* | *42.01* | *42.29* | *42.99* | *44.51* | *46.27* | *47.22* | *47.61* |
| Pichidegua | 182.00 | 182.00 | *176.74* | *159.29* | *160.36* | *163.00* | *168.76* | *175.43* | *179.06* | *180.54* |
| Curepto | 51.00 | 51.00 | *49.52* | *44.64* | *44.94* | *45.68* | *47.29* | *49.16* | *50.18* | *50.59* |
| Pencahue | 34.64 | 34.58 | *33.58* | *30.27* | *30.47* | *30.97* | *32.06* | *33.33* | *34.02* | *34.30* |
| Retiro | 242.14 | 686.54 | *666.68* | *600.88* | *604.90* | *614.87* | *636.60* | *661.76* | *675.44* | *681.02* |
| Yerbas Buenas | 60.00 | 486.79 | *472.71* | *426.05* | *428.90* | *435.98* | *451.38* | *469.22* | *478.92* | *482.87* |
| Cobquecura | 80.00 | 74.80 | *72.64* | *65.47* | *65.91* | *66.99* | *69.36* | *72.10* | *73.59* | *74.20* |
| Ninhue | 13.00 | 41.30 | *40.11* | *36.15* | *36.39* | *36.99* | *38.30* | *39.81* | *40.63* | *40.97* |
| Ñiquén | 20.00 | 41.30 | *40.11* | *36.15* | *36.39* | *36.99* | *38.30* | *39.81* | *40.63* | *40.97* |
| San Fabián | 28.00 | 28.00 | *27.19* | *24.51* | *24.67* | *25.08* | *25.96* | *26.99* | *27.55* | *27.77* |
| Ránquil | 60.00 | 47.50 | *46.13* | *41.57* | *41.85* | *42.54* | *44.04* | *45.79* | *46.73* | *47.12* |
| San Nicolás | 120.00 | 111.00 | *107.79* | *97.15* | *97.80* | *99.41* | *102.93* | *106.99* | *109.21* | *110.11* |
| San Ignacio | 12.00 | 12.00 | *11.65* | *10.50* | *10.57* | *10.75* | *11.13* | *11.57* | *11.81* | *11.90* |
| Quilaco | 48.00 | 64.60 | *62.73* | *56.54* | *56.92* | *57.86* | *59.90* | *62.27* | *63.56* | *64.08* |
| Contulmo | 84.75 | 78.35 | *76.08* | *68.57* | *69.03* | *70.17* | *72.65* | *75.52* | *77.08* | *77.72* |
| Galvarino | 192.06 | 244.63 | *237.55* | *214.11* | *215.54* | *219.09* | *226.84* | *235.80* | *240.68* | *242.66* |
| Toltén | 18.00 | 217.83 | *211.53* | *190.65* | *191.93* | *195.09* | *201.98* | *209.97* | *214.31* | *216.08* |
| Lago Ranco | 40.80 | 40.80 | *39.62* | *35.71* | *35.95* | *36.54* | *37.83* | *39.33* | *40.14* | *40.47* |
| Puerto Octay | 91.00 | 96.00 | *93.22* | *84.02* | *84.58* | *85.98* | *89.02* | *92.54* | *94.45* | *95.23* |
| Los Muermos | 30.00 | 30.00 | *29.13* | *26.26* | *26.43* | *26.87* | *27.82* | *28.92* | *29.52* | *29.76* |
| Cochamó | 70.23 | 70.20 | *68.17* | *61.44* | *61.85* | *62.87* | *65.09* | *67.67* | *69.07* | *69.64* |
| Quemchi | 16.00 | 35.00 | *33.99* | *30.63* | *30.84* | *31.35* | *32.45* | *33.74* | *34.43* | *34.72* |
| Quinchao | 80.00 | 240.00 | *233.06* | *210.06* | *211.46* | *214.95* | *222.54* | *231.34* | *236.12* | *238.07* |
| Puqueldón | 16.00 | 38.40 | *37.29* | *33.61* | *33.83* | *34.39* | *35.61* | *37.01* | *37.78* | *38.09* |
| Hualaihué | 20.00 | 158.40 | *153.82* | *138.64* | *139.56* | *141.87* | *146.88* | *152.68* | *155.84* | *157.13* |
| Cisnes | 92.84 | 101.43 | *98.50* | *88.77* | *89.37* | *90.84* | *94.05* | *97.77* | *99.79* | *100.61* |
| Maria Pinto | 89.62 | 106.02 | *102.95* | *90.11* | *90.71* | *92.20* | *95.46* | *99.24* | *101.29* | *102.12* |
| San Pedro | 7.60 | 27.18 | *26.39* | *23.78* | *23.94* | *24.34* | *25.20* | *26.19* | *26.74* | *26.96* |
| Alhué | 24.00 | 21.00 | *20.39* | *18.38* | *18.50* | *18.81* | *19.47* | *20.24* | *20.66* | *20.83* |
| TOTAL | 2,611.41 | 3,897.63 | *3,784.90* | *3,407.83* | *3,430.62* | *3,487.19* | *3,610.41* | *3,753.13* | *3,830.70* | *3,862.32* |
| | | | | | | | | | | |
| mean | 72.54 | 108.27 | *105.14* | *94.66* | *95.30* | *96.87* | *100.29* | *104.25* | *106.41* | *107.29* |
| stdev | 57.68 | 135.43 | *131.52* | *118.55* | *119.35* | *121.31* | *125.60* | *130.56* | *133.26* | *134.36* |

(*): Waste Generation 2001: (CONAMA, 2002d)
(**): Waste Generation 2002: (CONAMA, 2003)

Figure A21.1: Waste Generation Levels for the Represented Communes of Group 1 up to 2010

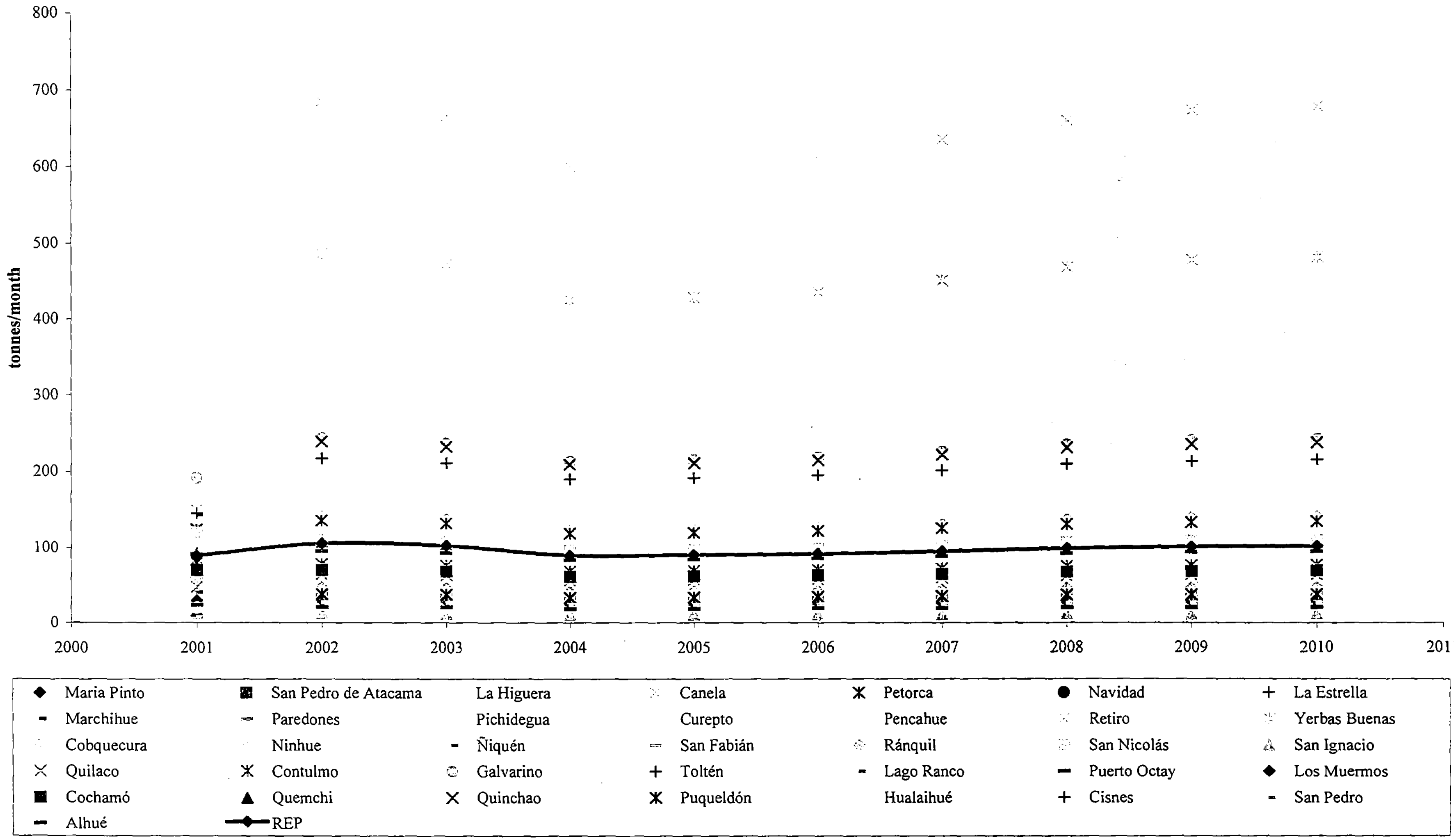


Table A21.2: Conversion Factors and Forecasted Levels of Waste Generation for the Represented Communes of Group 2

| **Group 2** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| ***Conversion Factors*** | | | ***0.34%*** | ***2.00%*** | ***3.00%*** | ***3.47%*** | ***2.85%*** | ***1.79%*** | ***1.00%*** | ***0.56%*** |
| (tonnes/month) | WG01 (*) | WG02 (**) | *WG03* | *WG04* | *WG05* | *WG06* | *WG07* | *WG08* | *WG09* | *WG10* |
| Representative Communes | 266.34 | 207.58 | *208.28* | *212.45* | *218.83* | *226.42* | *232.87* | *237.04* | *239.41* | *240.75* |
| Pozo Almonte | 15.00 | 15.00 | *15.05* | *15.35* | *15.81* | *16.36* | *16.83* | *17.13* | *17.30* | *17.40* |
| Vicuña | 584.50 | 584.50 | *586.49* | *598.22* | *616.18* | *637.55* | *655.72* | *667.45* | *674.14* | *677.91* |
| Monte Patria | 600.00 | 360.00 | *361.22* | *368.45* | *379.51* | *392.68* | *403.86* | *411.09* | *415.21* | *417.53* |
| Combarbalá | 250.00 | 180.00 | *180.61* | *184.22* | *189.76* | *196.34* | *201.93* | *205.55* | *207.61* | *208.77* |
| Salamanca | 540.00 | 540.00 | *541.83* | *552.67* | *569.27* | *589.02* | *605.79* | *616.64* | *622.82* | *626.30* |
| Cabildo | 248.00 | 273.00 | *273.93* | *279.41* | *287.80* | *297.78* | *306.26* | *311.74* | *314.87* | *316.63* |
| Putaendo | 240.22 | 540.00 | *541.83* | *552.67* | *569.27* | *589.02* | *605.79* | *616.64* | *622.82* | *626.30* |
| San Esteban | 272.66 | 408.00 | *409.39* | *417.58* | *430.11* | *445.03* | *457.71* | *465.90* | *470.57* | *473.20* |
| Catemu | 198.62 | 432.00 | *433.47* | *442.14* | *455.41* | *471.21* | *484.64* | *493.31* | *498.25* | *501.04* |
| Santa María | 155.00 | 420.00 | *421.43* | *429.86* | *442.76* | *458.12* | *471.17* | *479.61* | *484.41* | *487.12* |
| Hijuelas | 316.61 | 284.70 | *285.67* | *291.38* | *300.13* | *310.54* | *319.39* | *325.10* | *328.36* | *330.20* |
| Rinconada | 126.71 | 178.50 | *179.11* | *182.69* | *188.17* | *194.70* | *200.25* | *203.83* | *205.88* | *207.03* |
| Olmué | 78.58 | 236.39 | *237.19* | *241.94* | *249.20* | *257.85* | *265.19* | *269.94* | *272.64* | *274.17* |
| Peumo | 280.47 | 384.24 | *385.55* | *393.26* | *405.06* | *419.12* | *431.06* | *438.77* | *443.17* | *445.65* |
| Las Cabras | 375.00 | 375.00 | *376.27* | *383.80* | *395.32* | *409.04* | *420.69* | *428.22* | *432.51* | *434.93* |
| Pichilemu | 110.00 | 110.00 | *110.37* | *112.58* | *115.96* | *119.98* | *123.40* | *125.61* | *126.87* | *127.58* |
| Quinta de Tilcoco | 228.83 | 313.56 | *314.63* | *320.92* | *330.55* | *342.02* | *351.76* | *358.06* | *361.65* | *363.67* |
| Olivar | 248.03 | 339.84 | *340.99* | *347.82* | *358.26* | *370.69* | *381.25* | *388.07* | *391.96* | *394.15* |
| Codegua | 217.08 | 297.48 | *298.49* | *304.46* | *313.60* | *324.48* | *333.73* | *339.70* | *343.10* | *345.02* |
| Peralillo | 109.00 | 43.68 | *43.83* | *44.71* | *46.05* | *47.64* | *49.00* | *49.88* | *50.38* | *50.66* |
| Chépica | 274.63 | 288.68 | *289.66* | *295.45* | *304.32* | *314.88* | *323.85* | *329.65* | *332.95* | *334.81* |
| Licantén | 60.00 | 60.00 | *60.20* | *61.41* | *63.25* | *65.45* | *67.31* | *68.52* | *69.20* | *69.59* |
| Hualañé | 60.00 | 60.00 | *60.20* | *61.41* | *63.25* | *65.45* | *67.31* | *68.52* | *69.20* | *69.59* |
| Sagrada Familia | 209.44 | 160.65 | *161.20* | *164.42* | *169.36* | *175.23* | *180.22* | *183.45* | *185.29* | *186.32* |
| Teno | 130.68 | 697.20 | *699.57* | *713.56* | *734.99* | *760.48* | *782.15* | *796.15* | *804.12* | *808.62* |
| Longaví | 229.17 | 814.80 | *817.57* | *833.92* | *858.96* | *888.76* | *914.08* | *930.44* | *939.76* | *945.01* |
| Colbún | 143.38 | 509.75 | *511.49* | *521.72* | *537.38* | *556.02* | *571.86* | *582.10* | *587.93* | *591.22* |
| Quillón | 180.00 | 248.40 | *249.24* | *254.23* | *261.86* | *270.95* | *278.67* | *283.65* | *286.50* | *288.10* |
| Coihueco | 100.00 | 323.10 | *324.20* | *330.68* | *340.61* | *352.43* | *362.47* | *368.95* | *372.65* | *374.73* |
| Pinto | 143.35 | 111.30 | *111.68* | *113.91* | *117.33* | *121.40* | *124.86* | *127.10* | *128.37* | *129.09* |
| Santa Juana | 184.55 | 179.70 | *180.31* | *183.92* | *189.44* | *196.01* | *201.59* | *205.20* | *207.26* | *208.42* |
| Yumbel | 300.00 | 138.68 | *139.16* | *141.94* | *146.20* | *151.27* | *155.58* | *158.37* | *159.95* | *160.85* |
| Quilleco | 33.00 | 147.60 | *148.10* | *151.06* | *155.60* | *161.00* | *165.58* | *168.55* | *170.24* | *171.19* |
| Santa Bárbara | 180.00 | 371.60 | *372.86* | *380.32* | *391.74* | *405.33* | *416.88* | *424.34* | *428.59* | *430.99* |
| Negrete | 104.72 | 125.10 | *125.52* | *128.03* | *131.88* | *136.45* | *140.34* | *142.85* | *144.28* | *145.09* |
| Lebu | 363.41 | 520.70 | *522.47* | *532.92* | *548.92* | *567.96* | *584.14* | *594.60* | *600.56* | *603.91* |
| Renaico | 49.17 | 49.14 | *49.31* | *50.29* | *51.80* | *53.60* | *55.13* | *56.11* | *56.68* | *56.99* |
| Purén | 196.20 | 208.00 | *208.71* | *212.88* | *219.27* | *226.88* | *233.34* | *237.52* | *239.90* | *241.24* |
| Los Sauces | 40.83 | 40.86 | *41.00* | *41.82* | *43.07* | *44.57* | *45.84* | *46.66* | *47.13* | *47.39* |
| Carahue | 391.80 | 450.00 | *451.53* | *460.56* | *474.39* | *490.85* | *504.83* | *513.86* | *519.01* | *521.91* |
| Perquenco | 9.60 | 9.60 | *9.63* | *9.83* | *10.12* | *10.47* | *10.77* | *10.96* | *11.07* | *11.13* |
| Vilcún | 100.00 | 100.00 | *100.34* | *102.35* | *105.42* | *109.08* | *112.18* | *114.19* | *115.34* | *115.98* |
| Teodoro Schmidt | 51.00 | 45.00 | *45.15* | *46.06* | *47.44* | *49.08* | *50.48* | *51.39* | *51.90* | *52.19* |
| Freire | 164.50 | 164.50 | *165.06* | *168.36* | *173.42* | *179.43* | *184.54* | *187.85* | *189.73* | *190.79* |

**Group 2**

| *Conversion Factors* | | | ***0.34%*** | ***2.00%*** | ***3.00%*** | ***3.47%*** | ***2.85%*** | ***1.79%*** | ***1.00%*** | ***0.56%*** |
|---|---|---|---|---|---|---|---|---|---|---|
| (tonnes/month) | WG01 (*) | WG02 (**) | *WG03* | *WG04* | *WG05* | *WG06* | *WG07* | *WG08* | *WG09* | *WG10* |
| Representative Communes | 266.34 | 207.58 | *208.28* | *212.45* | *218.83* | *226.42* | *232.87* | *237.04* | *239.41* | *240.75* |
| Mariquina | 128.27 | 57.35 | *57.55* | *58.70* | *60.46* | *62.56* | *64.34* | *65.49* | *66.15* | *66.52* |
| Lanco | 106.33 | 47.55 | *47.71* | *48.66* | *50.12* | *51.86* | *53.34* | *54.29* | *54.84* | *55.14* |
| Máfil | 45.00 | 60.00 | *60.20* | *61.41* | *63.25* | *65.45* | *67.31* | *68.52* | *69.20* | *69.59* |
| Los Lagos | 135.00 | 96.46 | *96.79* | *98.72* | *101.69* | *105.22* | *108.21* | *110.15* | *111.25* | *111.88* |
| Paillaco | 107.00 | 92.04 | *92.35* | *94.20* | *97.03* | *100.39* | *103.25* | *105.10* | *106.16* | *106.75* |
| Río Negro | 42.00 | 90.00 | *90.31* | *92.11* | *94.88* | *98.17* | *100.97* | *102.77* | *103.80* | *104.38* |
| Fresia | 20.00 | 192.00 | *192.65* | *196.51* | *202.41* | *209.43* | *215.39* | *219.25* | *221.45* | *222.68* |
| Maullín | 30.00 | 144.00 | *144.49* | *147.38* | *151.80* | *157.07* | *161.55* | *164.44* | *166.08* | *167.01* |
| Calbuco | 240.00 | 187.50 | *188.14* | *191.90* | *197.66* | *204.52* | *210.35* | *214.11* | *216.26* | *217.46* |
| Quellón | 300.00 | 600.00 | *602.04* | *614.08* | *632.52* | *654.46* | *673.10* | *685.15* | *692.02* | *695.89* |
| Chaitén | 20.00 | 20.00 | *20.07* | *20.47* | *21.08* | *21.82* | *22.44* | *22.84* | *23.07* | *23.20* |
| Aisén | 740.00 | 700.00 | *702.38* | *716.43* | *737.94* | *763.54* | *785.29* | *799.34* | *807.35* | *811.87* |
| Natales | 250.00 | 250.00 | *250.85* | *255.87* | *263.55* | *272.69* | *280.46* | *285.48* | *288.34* | *289.95* |
| Tiltil | 620.41 | 507.00 | *508.72* | *518.90* | *534.48* | *553.02* | *568.77* | *578.95* | *584.76* | *588.02* |
| Calera de Tango | 627.20 | 566.40 | *568.32* | *579.69* | *597.10* | *617.81* | *635.41* | *646.78* | *653.27* | *656.92* |
| Coelemu | 360.00 | 218.91 | *219.65* | *224.05* | *230.77* | *238.78* | *245.58* | *249.98* | *252.48* | *253.89* |
| TOTAL | 12,081.35 | 15,334.06 | *15,386.17* | *15,693.98* | *16,165.12* | *16,725.91* | *17,202.37* | *17,510.26* | *17,685.74* | *17,784.61* |
| | | | | | | | | | | |
| mean | 211.08 | 266.16 | *267.06* | *272.40* | *280.58* | *290.32* | *298.59* | *303.93* | *306.98* | *308.69* |
| stdev | 170.29 | 200.52 | *201.21* | *205.23* | *211.39* | *218.73* | *224.96* | *228.98* | *231.28* | *232.57* |

(*): Waste Generation 2001: (CONAMA, 2002d)
(**): Waste Generation 2002: (CONAMA, 2003)

Figure A21.2: Waste Generation Levels for the Represented Communes of Group 2 up to 2010

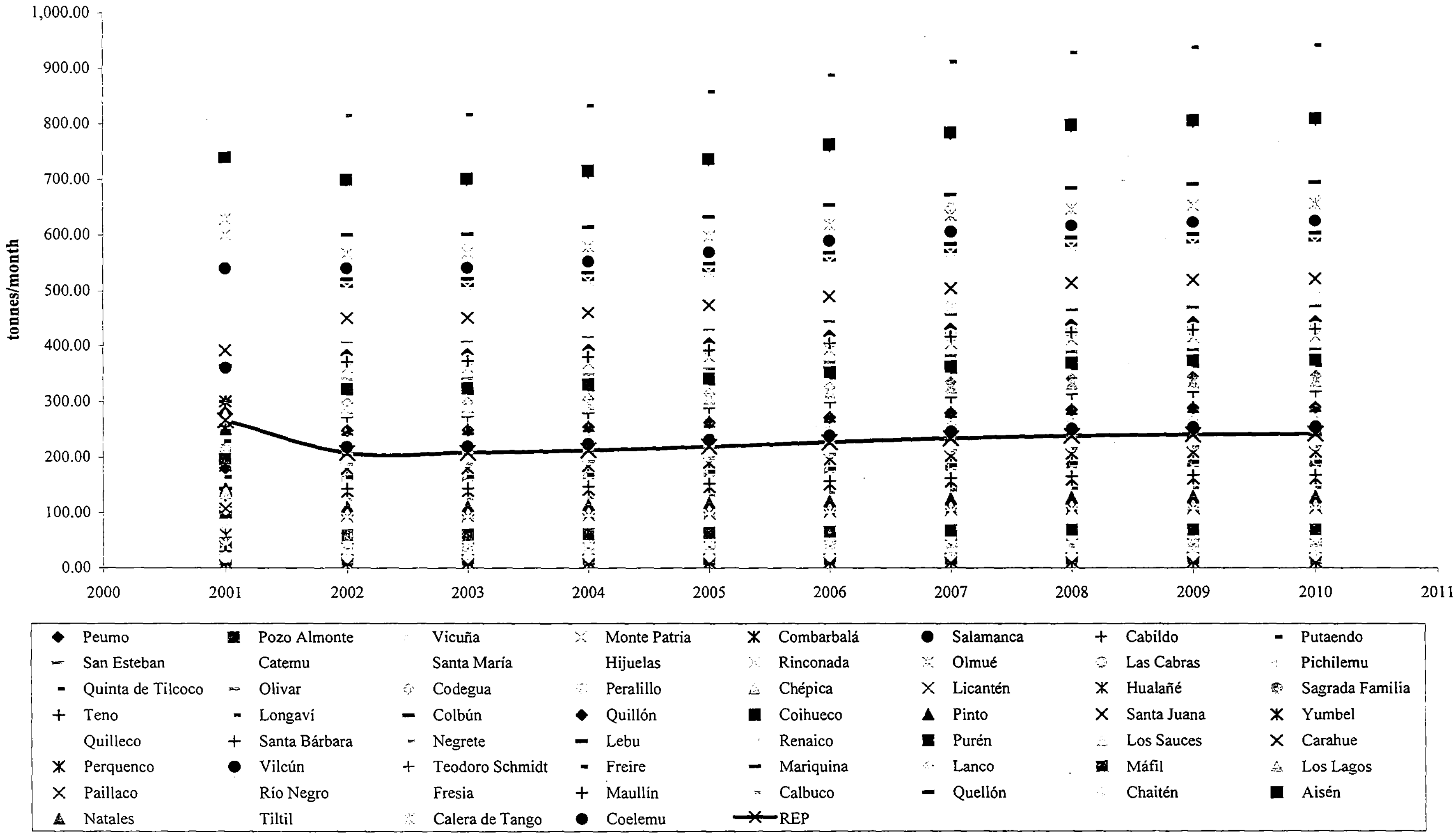


Table A21.3: Conversion Factors and Forecasted Levels of Waste Generation for the Represented Communes of Group 3

| **Group 3** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| ***Conversion Factors*** | | | ***-4.40%*** | ***-0.01%*** | ***0.03%*** | ***6.17%*** | ***5.93%*** | ***-1.18%*** | ***-2.31%*** | ***-2.86%*** |
| (tonnes/month) | WG01 (*) | WG02 (**) | *WG03* | *WG04* | *WG05* | *WG06* | *WG07* | *WG08* | *WG09* | *WG10* |
| Representative Commune | 2,901.42 | 2,830.25 | *2,705.75* | *2,705.38* | *2,706.14* | *2,873.20* | *3,043.65* | *3,007.61* | *2,938.19* | *2,854.12* |
| Iquique | 6,600.00 | 6,600.00 | *6,309.67* | *6,308.82* | *6,310.58* | *6,700.16* | *7,097.65* | *7,013.59* | *6,851.70* | *6,655.67* |
| Tocopilla | 903.87 | 750.00 | *717.01* | *716.91* | *717.11* | *761.38* | *806.55* | *797.00* | *778.60* | *756.33* |
| Calama | 2,125.00 | 3,300.00 | *3,154.83* | *3,154.41* | *3,155.29* | *3,350.08* | *3,548.82* | *3,506.79* | *3,425.85* | *3,327.84* |
| Antofagasta | 15,651.00 | 18,331.00 | *17,524.62* | *17,522.26* | *17,527.16* | *18,609.19* | *19,713.18* | *19,479.71* | *19,030.08* | *18,485.63* |
| Diego de Almagro | 120.00 | 288.00 | *275.33* | *275.29* | *275.37* | *292.37* | *309.72* | *306.05* | *298.98* | *290.43* |
| Copiapó | 5,000.00 | 5,000.00 | *4,780.05* | *4,779.41* | *4,780.74* | *5,075.88* | *5,377.01* | *5,313.32* | *5,190.68* | *5,042.18* |
| Vallenar | 615.00 | 1,560.00 | *1,491.38* | *1,491.18* | *1,491.59* | *1,583.67* | *1,677.63* | *1,657.76* | *1,619.49* | *1,573.16* |
| La Serena | 3,729.17 | 5,751.84 | *5,498.82* | *5,498.08* | *5,499.61* | *5,839.13* | *6,185.53* | *6,112.28* | *5,971.20* | *5,800.36* |
| Coquimbo | 3,735.34 | 5,808.00 | *5,552.51* | *5,551.76* | *5,553.31* | *5,896.14* | *6,245.93* | *6,171.96* | *6,029.50* | *5,856.99* |
| Ovalle | 1,625.00 | 1,957.00 | *1,870.91* | *1,870.66* | *1,871.18* | *1,986.70* | *2,104.56* | *2,079.64* | *2,031.63* | *1,973.51* |
| Quintero | 310.00 | 587.00 | *561.18* | *561.10* | *561.26* | *595.91* | *631.26* | *623.78* | *609.39* | *591.95* |
| Calera | 978.73 | 854.10 | *816.53* | *816.42* | *816.65* | *867.06* | *918.50* | *907.62* | *886.67* | *861.30* |
| Limache | 218.50 | 675.40 | *645.69* | *645.60* | *645.78* | *685.65* | *726.33* | *717.72* | *701.16* | *681.10* |
| Viña del Mar | 8,304.00 | 8,281.59 | *7,917.28* | *7,916.22* | *7,918.43* | *8,407.27* | *8,906.03* | *8,800.55* | *8,597.42* | *8,351.45* |
| Villa Alemana | 1,837.22 | 1,134.97 | *1,085.04* | *1,084.89* | *1,085.20* | *1,152.19* | *1,220.54* | *1,206.09* | *1,178.25* | *1,144.54* |
| San Antonio | 1,646.54 | 3,472.11 | *3,319.37* | *3,318.92* | *3,319.85* | *3,524.80* | *3,733.91* | *3,689.68* | *3,604.52* | *3,501.39* |
| Rancagua | 4,310.01 | 5,905.44 | *5,645.66* | *5,644.90* | *5,646.48* | *5,995.06* | *6,350.72* | *6,275.50* | *6,130.65* | *5,955.26* |
| San Fernando | 1,263.09 | 1,327.70 | *1,269.29* | *1,269.12* | *1,269.48* | *1,347.85* | *1,427.81* | *1,410.90* | *1,378.33* | *1,338.90* |
| Curicó | 1,549.77 | 3,267.60 | *3,123.86* | *3,123.44* | *3,124.31* | *3,317.19* | *3,513.98* | *3,472.36* | *3,392.22* | *3,295.16* |
| Talca | 6,000.00 | 5,400.00 | *5,162.45* | *5,161.76* | *5,163.20* | *5,481.95* | *5,807.17* | *5,738.39* | *5,605.94* | *5,445.55* |
| Linares | 677.46 | 2,408.66 | *2,302.70* | *2,302.39* | *2,303.04* | *2,445.21* | *2,590.27* | *2,559.60* | *2,500.52* | *2,428.98* |
| Chillán | 1,982.00 | 5,104.00 | *4,879.47* | *4,878.82* | *4,880.18* | *5,181.46* | *5,488.85* | *5,423.84* | *5,298.65* | *5,147.05* |
| Tomé | 1,025.00 | 1,260.00 | *1,204.57* | *1,204.41* | *1,204.75* | *1,279.12* | *1,355.01* | *1,338.96* | *1,308.05* | *1,270.63* |
| Concepción | 5,337.27 | 5,220.00 | *4,990.37* | *4,989.70* | *4,991.10* | *5,299.22* | *5,613.59* | *5,547.11* | *5,419.07* | *5,264.03* |
| Talcahuano | 6,789.04 | 6,048.00 | *5,781.95* | *5,781.17* | *5,782.79* | *6,139.78* | *6,504.03* | *6,427.00* | *6,278.65* | *6,099.02* |
| San Pedro de la Paz | 1,987.25 | 1,944.00 | *1,858.48* | *1,858.23* | *1,858.75* | *1,973.50* | *2,090.58* | *2,065.82* | *2,018.14* | *1,960.40* |
| Chiguayante | 2,008.37 | 1,962.00 | *1,875.69* | *1,875.44* | *1,875.96* | *1,991.77* | *2,109.94* | *2,084.95* | *2,036.82* | *1,978.55* |
| Coronel | 1,386.71 | 1,949.00 | *1,863.26* | *1,863.01* | *1,863.53* | *1,978.58* | *2,095.96* | *2,071.13* | *2,023.33* | *1,965.44* |
| Lota | 712.59 | 971.49 | *928.76* | *928.63* | *928.89* | *986.24* | *1,044.74* | *1,032.37* | *1,008.54* | *979.69* |
| Los Angeles | 1,673.55 | 1,126.93 | *1,077.36* | *1,077.21* | *1,077.52* | *1,144.04* | *1,211.91* | *1,197.55* | *1,169.91* | *1,136.44* |
| Curanilahue | 463.69 | 713.02 | *681.66* | *681.56* | *681.75* | *723.84* | *766.78* | *757.70* | *740.21* | *719.04* |
| Angol | 1,600.00 | 1,713.00 | *1,637.64* | *1,637.42* | *1,637.88* | *1,739.00* | *1,842.16* | *1,820.34* | *1,778.33* | *1,727.45* |
| Valdivia | 1,851.00 | 3,392.00 | *3,242.79* | *3,242.35* | *3,243.26* | *3,443.48* | *3,647.76* | *3,604.56* | *3,521.36* | *3,420.61* |
| Osorno | 2,068.33 | 5,094.32 | *4,870.22* | *4,869.57* | *4,870.93* | *5,171.63* | *5,478.44* | *5,413.55* | *5,288.60* | *5,137.29* |
| Puerto Montt | 5,490.20 | 5,490.00 | *5,248.49* | *5,247.79* | *5,249.26* | *5,573.31* | *5,903.95* | *5,834.03* | *5,699.37* | *5,536.31* |
| Colina | 5,603.06 | 2,676.70 | *2,558.95* | *2,558.61* | *2,559.32* | *2,717.32* | *2,878.53* | *2,844.44* | *2,778.78* | *2,699.28* |
| Melipilla | 95.16 | 340.34 | *325.37* | *325.32* | *325.42* | *345.50* | *366.00* | *361.67* | *353.32* | *343.21* |
| Buin | 2,181.32 | 1,971.00 | *1,884.30* | *1,884.04* | *1,884.57* | *2,000.91* | *2,119.62* | *2,094.51* | *2,046.17* | *1,987.63* |
| San Bernardo | 8,487.47 | 8,489.00 | *8,115.57* | *8,114.48* | *8,116.75* | *8,617.83* | *9,129.08* | *9,020.96* | *8,812.74* | *8,560.61* |
| Padre Hurtado | 1,333.44 | 1,204.80 | *1,151.80* | *1,151.65* | *1,151.97* | *1,223.08* | *1,295.64* | *1,280.30* | *1,250.75* | *1,214.96* |
| Peñaflor | 2,291.39 | 2,070.60 | *1,979.51* | *1,979.25* | *1,979.80* | *2,102.02* | *2,226.73* | *2,200.35* | *2,149.57* | *2,088.07* |
| El Monte | 26.63 | 95.25 | *91.06* | *91.05* | *91.07* | *96.70* | *102.43* | *101.22* | *98.88* | *96.05* |
| Talagante | 2,117.21 | 2,057.90 | *1,967.37* | *1,967.11* | *1,967.66* | *2,089.13* | *2,213.07* | *2,186.86* | *2,136.38* | *2,075.26* |
| Lo Barnechea | 3,142.87 | 2,571.40 | *2,458.28* | *2,457.95* | *2,458.64* | *2,610.42* | *2,765.29* | *2,732.54* | *2,669.46* | *2,593.09* |
| Las Condes | 10,507.33 | 8,596.90 | *8,218.72* | *8,217.62* | *8,219.91* | *8,727.36* | *9,245.12* | *9,135.62* | *8,924.76* | *8,669.42* |
| La Reina | 4,068.58 | 3,329.30 | *3,182.84* | *3,182.42* | *3,183.31* | *3,379.82* | *3,580.33* | *3,537.93* | *3,456.27* | *3,357.38* |
| Peñalolén | 9,084.74 | 23,650.60 | *22,610.21* | *22,607.17* | *22,613.49* | *24,009.51* | *25,433.88* | *25,132.66* | *24,552.56* | *23,850.10* |
| La Florida | 12,577.50 | 11,364.00 | *10,864.10* | *10,862.64* | *10,865.67* | *11,536.46* | *12,220.86* | *12,076.12* | *11,797.39* | *11,459.86* |

Table A21.3: Conversion Factors and Forecasted Levels of Waste Generation for the Represented Communes of Group 3

**Group 3**

| ***Conversion Factors*** | | | ***-4.40%*** | ***-0.01%*** | ***0.03%*** | ***6.17%*** | ***5.93%*** | ***-1.18%*** | ***-2.31%*** | ***-2.86%*** |
|---|---|---|---|---|---|---|---|---|---|---|
| (tonnes/month) | WG01 (*) | WG02 (**) | *WG03* | *WG04* | *WG05* | *WG06* | *WG07* | *WG08* | *WG09* | *WG10* |
| Huechuraba | 3,114.44 | 2,548.00 | *2,435.91* | *2,435.59* | *2,436.27* | *2,586.67* | *2,740.12* | *2,707.67* | *2,645.17* | *2,569.49* |

**Group 3**

| ***Conversion Factors*** | | | ***-4.40%*** | ***-0.01%*** | ***0.03%*** | ***6.17%*** | ***5.93%*** | ***-1.18%*** | ***-2.31%*** | ***-2.86%*** |
|---|---|---|---|---|---|---|---|---|---|---|
| (tonnes/month) | WG01 (*) | WG02 (**) | *WG03* | *WG04* | *WG05* | *WG06* | *WG07* | *WG08* | *WG09* | *WG10* |
| Representative Commune | 2,901.42 | 2,830.25 | *2,705.75* | *2,705.38* | *2,706.14* | *2,873.20* | *3,043.65* | *3,007.61* | *2,938.19* | *2,854.12* |
| La Pintana | 6,538.05 | 5,907.60 | *5,647.72* | *5,646.97* | *5,648.54* | *5,997.25* | *6,353.04* | *6,277.80* | *6,132.90* | *5,957.43* |
| San Miguel | 3,316.35 | 2,713.10 | *2,593.75* | *2,593.40* | *2,594.13* | *2,754.27* | *2,917.67* | *2,883.12* | *2,816.57* | *2,735.99* |
| San Ramón | 2,901.42 | 2,830.25 | *2,705.75* | *2,705.38* | *2,706.14* | *2,873.20* | *3,043.65* | *3,007.61* | *2,938.19* | *2,854.12* |
| La Cisterna | 3,578.98 | 2,928.90 | *2,800.06* | *2,799.68* | *2,800.46* | *2,973.35* | *3,149.74* | *3,112.44* | *3,040.60* | *2,953.61* |
| El Bosque | 6,039.62 | 5,457.00 | *5,216.95* | *5,216.25* | *5,217.70* | *5,539.81* | *5,868.46* | *5,798.96* | *5,665.11* | *5,503.03* |
| Lo Espejo | 3,879.80 | 3,505.80 | *3,351.58* | *3,351.13* | *3,352.07* | *3,559.00* | *3,770.14* | *3,725.49* | *3,639.50* | *3,535.37* |
| Recoleta | 6,232.25 | 5,098.60 | *4,874.31* | *4,873.66* | *4,875.02* | *5,175.97* | *5,483.04* | *5,418.10* | *5,293.04* | *5,141.61* |
| Providencia | 5,082.43 | 4,158.70 | *3,975.76* | *3,975.22* | *3,976.34* | *4,221.81* | *4,472.27* | *4,419.30* | *4,317.30* | *4,193.78* |
| Macul | 4,731.79 | 7,368.86 | *7,044.70* | *7,043.75* | *7,045.72* | *7,480.69* | *7,924.48* | *7,830.63* | *7,649.88* | *7,431.02* |
| Conchalí | 5,603.06 | 4,583.80 | *4,382.16* | *4,381.57* | *4,382.79* | *4,653.36* | *4,929.42* | *4,871.04* | *4,758.61* | *4,622.47* |
| Independencia | 2,753.22 | 2,252.90 | *2,153.79* | *2,153.51* | *2,154.11* | *2,287.09* | *2,422.77* | *2,394.08* | *2,338.82* | *2,271.90* |
| San Joaquín | 4,104.87 | 3,359.20 | *3,211.43* | *3,211.00* | *3,211.89* | *3,410.18* | *3,612.49* | *3,569.70* | *3,487.31* | *3,387.54* |
| La Granja | 4,558.08 | 4,118.40 | *3,937.23* | *3,936.70* | *3,937.80* | *4,180.90* | *4,428.93* | *4,376.48* | *4,275.46* | *4,153.14* |
| Quilicura | 5,319.74 | 4,352.40 | *4,160.94* | *4,160.38* | *4,161.54* | *4,418.45* | *4,680.58* | *4,625.14* | *4,518.39* | *4,389.11* |
| Renca | 5,614.07 | 4,592.90 | *4,390.86* | *4,390.27* | *4,391.50* | *4,662.60* | *4,939.21* | *4,880.71* | *4,768.06* | *4,631.64* |
| Quinta Normal | 4,373.42 | 3,578.90 | *3,421.46* | *3,421.00* | *3,421.96* | *3,633.21* | *3,848.75* | *3,803.17* | *3,715.39* | *3,609.09* |
| Cerro Navia | 6,236.12 | 5,102.50 | *4,878.04* | *4,877.39* | *4,878.75* | *5,179.93* | *5,487.23* | *5,422.25* | *5,297.09* | *5,145.54* |
| Lo Prado | 4,386.21 | 3,589.30 | *3,431.41* | *3,430.95* | *3,431.90* | *3,643.77* | *3,859.94* | *3,814.22* | *3,726.18* | *3,619.58* |
| Estación Central | 4,484.95 | 9,787.20 | *9,356.66* | *9,355.40* | *9,358.02* | *9,935.73* | *10,525.17* | *10,400.51* | *10,160.45* | *9,869.76* |
| Cerrillos | 2,473.23 | 5,397.20 | *5,159.78* | *5,159.08* | *5,160.53* | *5,479.11* | *5,804.15* | *5,735.41* | *5,603.03* | *5,442.73* |
| Pudahuel | 8,226.68 | 6,731.40 | *6,435.29* | *6,434.42* | *6,436.22* | *6,833.55* | *7,238.95* | *7,153.22* | *6,988.11* | *6,788.18* |
| Maipú | 16,110.45 | 16,113.50 | *15,404.67* | *15,402.60* | *15,406.90* | *16,358.03* | *17,328.47* | *17,123.25* | *16,728.02* | *16,249.42* |
| TOTAL | 282,750.60 | 309,142.36 | *295,543.16* | *295,503.45* | *295,586.07* | *313,833.81* | *332,452.02* | *328,514.73* | *320,932.03* | *311,750.12* |
| | | | | | | | | | | |
| mean | 3,982.40 | 4,354.12 | *4,162.58* | *4,162.02* | *4,163.18* | *4,420.19* | *4,682.42* | *4,626.97* | *4,520.17* | *4,390.85* |
| stdev | 3,337.97 | 4,034.35 | *3,856.88* | *3,856.36* | *3,857.44* | *4,095.58* | *4,338.55* | *4,287.17* | *4,188.21* | *4,068.39* |

(*): Waste Generation 2001: (CONAMA, 2002d)
(**): Waste Generation 2002: (CONAMA, 2003)

Figure A21.3: Waste Generation Levels for the Represented Communes of Group 3 up to 2010